RISK, UNCERTAINTY, AND FINANCIAL MARKETS

Cathy S. Goldberg, School of Business, University of San Francisco, 2130 Fulton Street, San Francisco, CA 94117, 415-422-5555, goldberg@usfca.edu
Robert N. Mefford, School of Business, University of San Francisco, 2130 Fulton Street, San Francisco, CA 94117, 415-422-5555, mefford@usfca.edu
Antonia Sottile, International and Development Economics, University of San Francisco, 2130 Fulton Street, San Francisco, CA 94117, 415-422-5555, amsottile@dons.usfca.edu

ABSTRACT

Recent experiences in asset market pricing are anomalous in regards to the relationship between return and risk. This paper examines a potential missing ingredient that may help clarify the relationship between risk and return—that is, the role of uncertainty. Uncertainty is differentiated from risk in several key dimensions and is hypothesized to have differential effects on market participant behavior. These effects are difficult to ascertain because uncertainty is often considered unmeasurable. In this paper, we use the VVIX as a potential proxy measure of uncertainty in analyzing U.S. equity returns. We run our analysis over two time periods of financial market turbulence: the global financial crisis and the COVID pandemic. Using a VAR specification, we obtain significant results for both periods. Additional statistical tests indicate that the VVIX may be used to predict movements in equity returns as measured by the SPY ETF. Our findings suggest that the joint effect of risk and uncertainty on market sentiment, and thus equity returns, is more important than either individually.

Keywords: risk, uncertainty, ambiguity, portfolio risk, asset management

INTRODUCTION

In recent years there has been a surfeit of economic and political turmoil throughout the world. From the rise of populism in Europe and the U.S., the continuing conflicts of the Middle East, and the pandemic beginning in 2020, the world has become a very uncertain place. Yet the financial markets have reacted, except for brief interludes, with rising asset prices and falling volatility. For example, the U.S. equity markets have achieved new highs yet volatility, as measured by the VIX, after spiking during the early pandemic, has fallen back to slightly above its historic average of about 20. One would expect that with all the political and economic uncertainty that a high degree of risk aversion would hold and that the VIX would reflect this by rising (it is often referred to as the *fear gauge*). Modern Portfolio Theory (MPT) argues that higher risk must be rewarded with higher return, but yet risk, as measured as volatility, has fallen. This puzzling return-to-risk relationship is difficult to explain with traditional financial theories.

One possible answer to this dilemma is to consider uncertainty as an intervening variable. Although uncertainty is often thought to express itself through risk aversion, it should be considered separate and distinct from risk. The conventional financial definition of *risk* is volatility of an asset's price. The more volatile the asset, the higher the return expected to compensate for this risk. This definition provides for a way to measure risk through the variance of an asset's return. Historical return of the asset price is typically used to generate the volatility measure. Of course, historical volatility is not always a good predictor of future volatility so other measures have been developed that attempt to generate forward-looking volatility forecasts. One of the most common of these is the VIX which is extracted from option prices on the S&P 500 index. It provides a 30 day ahead forecast of volatility. Other longer-term volatility forecasts such as variance swaps are available as well. The VIX itself is not a tradeable investment product, but derivatives using futures and options on the VIX are available, and their volume has increased dramatically in recent years as a way to speculate on or hedge volatility trends. Why have not the prices of the long versions of these instruments risen to reflect the high level of political and economic uncertainty that exist currently? Cascaldi-Garcia, et al (2020) provide a chart (Figure 31) of how risk, measured by the VIX, and uncertainty, measured by an ambiguity proxy, have diverged in the last few years.

Uncertainty in financial markets could be defined as ambiguity about what asset prices will be in the future. More precisely, uncertainty is ambiguity about the probability distribution for future asset prices. The terms uncertainty and ambiguity are often used interchangeably in the finance and economics literature, and we will do so also in this paper. Unlike risk, which is conventionally primarily concerned with downside price movements, uncertainty is agnostic, equally concerned with upside and downside price movements, but not having an expectation of which direction this movement will be. Therefore, the natural tendency is to postpone making a decision until the direction of change becomes clearer. In efficient market terminology, the current level of prices reflects the best possible estimate of the future price as all relevant information is expressed in that price. Consequently, the rational course of action is no action; wait until new information (news) is available before making a decision. Such inaction would be expressed in low volumes of trading and low volatility. These indicators provide possible measures of uncertainty which is usually considered unmeasurable. However, investors may not react to uncertainty with inertia; they may instead react with increased trading depending on their uncertainty-aversion or uncertainty-seeking predilection. We will discuss this topic below.

If appropriate proxies for uncertainty can be found, then they may be useful in predicting asset prices in financial markets, supplementing volatility and other forecasting factors using economic variables. Such forecasts could be used for asset allocation decisions and portfolio rebalancing as well as deciding when hedging might be necessary. Uncertainty forecasts might also be used to predict future macroeconomic events and the effect on financial markets.

This paper is organized as follows: Section 2 provides a literature review of relevant work on the relationships between risk and financial markets as well as the limited amount of work on uncertainty and the markets. Section 3 discusses the hypothesized relationship of uncertainty on financial markets as well as potential measures of uncertainty. Section 4 discusses our data and methodology used to examine the relationship between uncertainty and asset returns. In Section 5, we present our empirical results. Section 6 concludes our study and proposes ideas for future research.

LITERATURE REVIEW

The extensive literature on the relationship between return and risk will not be reviewed here, only the most salient work. The basic tenets of Modern Portfolio Theory (MPT) that relates return to risk were proposed by Markowitz (1952) and have become the bedrock of investment theory since. In recent years some criticism has arisen of the iron-clad linkage of return to risk in MPT. Many of the anomalies such as the small firm, value, and momentums effects noted by Fama and French (1993 and 2015), Jegadeesh and Titman, 1993, and others are difficult to explain using MPT. The increasing skepticism of the validity of MPT has led to the development of new investment approaches emphasizing smart beta strategies that do not mimic the market capitalization portfolio instead emphasizing quality or value factors, momentum, or low volatility to structure portfolios (Asness, et al, 2013; Moskowitz, et al, 2012). The last variation that picks stocks based on low volatility is directly contrary to MPT by relating higher returns to low, not high, volatility (Moreira and Muir, 2017).

The widespread acceptance of the return-to-risk relationship in MPT is starting to weaken. This has led to attempts to explain if, and when, the relationship does actually hold. One such path focuses on uncertainty and how it might influence both asset prices and risk aversion. Uncertainty as a relevant variable independent from risk has frequently been neglected and is often comingled with risk; in fact, many have viewed them as one and the same. Some researchers have actually used risk measures such as the VIX as a proxy for uncertainty. If they are different, and have differing effects on asset prices, this is clearly inappropriate.

Financial research has found that economic policy uncertainly can increase stock volatility, stock co-movement, and equity premiums (Pastor and Veronesi, 2012; Pastor and Veronese, 2013; Brogaard and Detzel, 2015). Several articles have proposed that increases in ambiguity reduce trading in stocks and options (Ben-Rephael and Izhakin, 2020) and also reduce liquidity (Ozsoylev and Werner, 2011; Routledge and Zin, 2009). The relationship of market sentiment to ambiguity and the effect on market returns has been explored in some recent articles. Birru and Young (2020) found that sentiment has a greater effect on asset prices when ambiguity is high. Bali, et al (2017) separated stocks into two categories, those with positive economic uncertainty betas and those with negative betas; i.e., the positive uncertainty beta stocks vary positively with economic uncertainty whereas the negative beta stocks vary inversely. They found that the positive uncertainty beta stocks underperformed the negative beta stocks and attribute this to an uncertainty premium required of the negative beta stocks. Nartea, et al (2021) find that the negative investor uncertainty premium is only present when investor sentiment is low. In periods of high investor sentiment, it disappears.

Brenner and Izhakian (2018) develop a model to separately measure risk and uncertainty and find the MPT's expected positive return to risk relationship holds when they include their ambiguity proxy. Their proxy measures ambiguity by the volatility of the risk probabilities of returns of the S&P 500 index ETF and find that this ambiguity measure is part of the equity premium, which not only represents risk (volatility) but also ambiguity (volatility of volatility). They also find that the correlation between risk and their ambiguity measure varies from being highly negative to positive depending on market conditions, being negative in calm markets and positive in stressed markets. Including an ambiguity component in the equity risk premium might also explain the "equity premium puzzle" (Mehra and Prescott, 1985) where risk premiums in many markets do not appear to be justified solely by using variance as a measure of risk (Chen and Epstein, 2002).

There is a body of research that separates investors into ambiguity-averse and ambiguity-seeking categories. This approach proposes that these types of investors will react differently to an increase in ambiguity in an investment situation. Dimmock, et al, 2016 found in a large survey that 52% of investors are ambiguity-averse while 38% are ambiguity-seeking (with 10% as ambiguity-neutral). The ambiguity-averse investors are less likely to own equities, particularly foreign equites, and have a bias toward own-company stock ownership and under-diversification. They were also more likely to sell stocks during the financial crisis of 2008-9 than ambiguity-seeking investors. Epstein and Scheider (2008) propose a model in which ambiguity-averse investors react more strongly to bad news than good news. Thus, it is difficult to predict a priori how investors will react to an increase in ambiguity. Some may choose to not participate in markets (inertia) holding existing positions and not trading while others may increase either buying or selling of different types of assets depending on their degree of ambiguity aversion or seeking. The nature of the increase in ambiguity, whether economic, political, or financial, also will influence investor actions. The interaction of ambiguity aversion and risk aversion also may be an important determinant of investor behaviors. Therefore, it really becomes an empirical question of how changes in ambiguity influence financial markets.

UNCERTAINTY AND FINANCIAL MARKETS

Effects of Uncertainty on Financial Markets

There are several potential effects of increased uncertainty on financial markets and asset prices. If trading volume is reduced because of greater uncertainty (Azi, et al, 2022) liquidity will likely also be reduced resulting in wider spreads on bid-ask prices. This is turn could lead to further falls in trading and increases in spreads. The effect on volatility of prices could theoretically be either an increase or decrease depending on how investors react to a reduction in trading and liquidity. Risk adverse investors may perceive this as a risky environment and increase selling which could cause an increase in volatility. Or they might choose to lay on more financial hedges such as put options which can create a stabilizing force as banks hedge their own positions when buying or selling puts and calls, creating a feedback loop (The Wall Street Journal, April 7, 2017). This hedging activity decreases volatility.

Ambiguity could also have momentum effects on markets where increased uncertainty may lead to increased *herding* behavior as ambiguity-averse investors "follow the crowd" as they trust collective judgement in an uncertain market. If excess herding leads to *crowding,* then market liquidity could also dry up, increasing price volatility.

On the other hand, investors might refrain from trading. Epstein and Schneider (2010) suggest increased ambiguity could lead to investor inertia and "trading freezes". The "central tendency effect" (Enke and Graeber, 2020), where decision-makers lacking confidence in their ability to make a good decision, revert to assessing probabilities as "50-50" or the mean of a probability distribution, which could retard trading activity. Reduced trading leads to less liquid markets which could potentially increase price movements. Therefore, the effect of uncertainty on trading, liquidity, and volatility are empirical question that remain to be answered. Portfolio decisions about categories of assets could also be influenced by ambiguity; for example, the well-known "home-bias effect" where investors prefer assets that they are more familiar with.

Another possible effect of ambiguity in financial markets is to bring to the fore behavioral tendencies that might be less prevalent in stable and less uncertain markets. For example, the "representativeness bias" of Kahneman and Tversky (1972) where investors assume the recent past will continue into the future. With high ambiguity this might lead investors to continue with the same investment strategies they have been using in the past, leading to boom and bust cycles because of the persistence of this inertia too long (Gennaioli, et al, 2015). Another potential behavioral phenomenon related to ambiguity is "overconfidence". Numerous studies have shown that investors, even professional investors, are often overconfident of their predictive abilities (Daniel and Hirshleifer, 2015). With increased uncertainty such investors may become even more over-confident and trade more frequently and take riskier bets.

There may also be macroeconomic consequences of increased uncertainty in financial markets. If greater ambiguity about asset prices also stimulates increased uncertainty about economic growth, consumption and investment could also be put on hold (Bansal, et al, 2019). If volatility of asset prices increases, for reasons explained previously, this would also tend to deter some investment and consumption decisions by both businesses and consumers. The greater macroeconomic uncertainty that results might also increase the financial market ambiguity, reinforcing it. Therefore, increases in financial uncertainty and macroeconomic uncertainty could be mutually reinforcing.

Since the potential effects of changes in uncertainty can be significant, affecting both asset prices and volatility, it would be useful to have a proxy measure for uncertainty/ambiguity. If such a measure is useful for forecasting, it could improve portfolio risk management. To this topic we now turn.

Potential Measures of Uncertainty

Knightian uncertainty is unmeasurable; by definition no probability distribution can be assigned to it. This suggests that proxies must be found that would fluctuate with the degree of ambiguity. Attempts have been made to find such proxies, and there are several major categories of uncertainty measures: news-based, survey-based, econometric, and asset-market based. One type of survey proxy uses counts of words considered to represent uncertainty in the press. The Economic Policy Uncertainty (EPU) index is one such widely used indicator of macroeconomic uncertainty. It was developed by Baker, et al (2016). The latest version combines the word counts from the press with a measure of changes in the U.S. tax code and the magnitude of disagreement in economic forecasts. Similar indices have been developed for other countries as well. There are other measures for macroeconomic uncertainty which focus on monetary policy, trade policy, world economic events, and geopolitical risk some of which use econometric methods as well as news and surveys. Cascaldi-Garcia, et al (2020) provide a comprehensive survey of the various measures used as well as the asset-market based ones to be discussed next. Kozeniauskas, Orlik, and Veldkamp (2018) note that correlations among different measures of uncertainty are far from 1.0, averaging 0.32 for the measures tested, indicating they are measuring different types of uncertainty and should not be used interchangeably.

Another potential proxy for uncertainty could be the volatility of volatility itself as an indicator of ambiguity. Epstein and Ji (2014) and Brenner and Izhakian (2018) propose using the variance of variance as a measure of ambiguity. The premise is that is that the volatility of volatility increases when investors are increasingly uncertain about the risk distribution: i.e., the volatility of investment returns increases. For equity volatility such a measure exists, the VVIX of the CBOE which measures the 30 days ahead volatility of the VIX index. Although the VIX itself is often used as a measure of ambiguity, it is designed to be a measure of risk, and consequently is often called the "fear gauge". A measure of risk for interest rates is the Merrill-Lynch MOVE index which is extracted from interest rate options. The vol of vol of this index could also be a potential measure of uncertainty about future interest rates, although no such index is currently published. Coiculescu, et al, (2019) use the approach of measuring ambiguity as the volatility of volatility in a study of innovation, although not using the volatility of the VIX as their measure.

Several other approaches can be proposed as proxies for uncertainty. One of these is to measure trading volumes in financial markets testing the hypothesis that ambiguity leads to less trading, which should then lead to negative correlation between trading volume and uncertainty. Alternatively, one could measure liquidity through bid-ask spreads in asset markets, also relating higher ambiguity with less trading, and thus larger spreads. This approach has been applied in several studies (Ben-Rephael and Izhakain, 2020, Tan, et al, 2017). The jump risk premium that Andersen, et al (2016) extracts from deep OTM short-dated (weekly) options on the S&P 500 index (SPXW) also may be a potential indicator of uncertainty.

The advantage of options-based measures of uncertainty over news, survey, or econometric proxies is that it is both real time and forward looking. If uncertainty is unstable and can rapidly change, which seems likely, this is essential for forecasting financial market performance.

To develop a useful forecasting tool for uncertainty, we need to empirically determine which of the hypothetical effects of changes in uncertainty have on financial markets and asset prices. Specifically, we need to determine the econometric relationships among the variables: asset prices, volatility, and uncertainty. There are several uncertainty proxies that could be tested including the following:

Liquidity as measured by bid-ask spreads
Trading volumes
Vol of vol of equities as measured by the VVIX (CBOE)
Jump tail risk premium in SPXW (CBOE)
Vol of vol of interest rates as measured by the volatility of the MOVE index (Merrill-Lynch)

All of these measures use real time and readily available data so can be easily utilized in a portfolio risk management program. In our initial empirical tests we focus on the VVIX as our proxy measure of uncertainty. We also analyze the VIX as a measure of risk.

DATA AND METHODOLOGY

Data

Our sample selection uses daily data from *Yahoo Finance* spanning January 2007-June 2022.
We structure our analysis as two specific event studies each spanning five years during the periods January 2007-January 2012 and June 2017-June 2022. The first period contains the global financial crisis and the second spans COVID; both of these periods experienced high market turbulence.

Converting adjusted closing prices for the ETF's employed to returns, we examine how the U.S. stock market, as proxied by the S&P 500 (SPY), may be affected by our measure of uncertainty, the VVIX as well as a measure of risk, the VIX. Descriptive statistics for the variables used in our analysis are shown in Table 1 for the two time periods:

Table 1. Descriptive Statistics:

	January 2007-January 2012			***June 2017-June 2022***		
Measure	**SPY**	**VVIX**	**VIX**	**SPY**	**VVIX**	**VIX**
Mean	0.0141%	0.1193%	0.3414%	0.0498%	0.1658%	0.4868%
Standard Deviation	1.6727%	4.9522%	7.8421%	1.2715%	5.2630%	9.4202%
Skewness	0.2566	2.1086	1.4448	-0.7116	2.0337	2.8286
Kurtosis	9.7921	16.2428	6.8709	14.0163	11.9580	21.8632

Methodology

Our approach is consistent with the study conducted by Tan, et al, (2017) when examining how ambiguity might impact the UK stock market. Using a VAR model to explore the relationship between the VVIX and SPY as well as the VIX and SPY, we are able to discover relationships between the ambiguity and risk measures and the US stock market by running the following system of equations:

(1) $r_t = r_{t-1} + r_{t-2} + \ldots + r_{t-p} + a_t - 1 + a_{t-2} + \ldots + a_{t-p} + \varepsilon_t$
(2) $a_t = r_{t-1} + r_{t-2} + \ldots + r_{t-p} + a_t - 1 + a_{t-2} + \ldots + a_{t-p} + \varepsilon_t$

Where **r** represents the daily return of the S&P ETF (SPY), **a** represents the daily percentage change in the VVIX/VIX, and **p** represents the order of lags used in the equation as determined by Akaike information criterion (AIC).

RESULTS

In order to run our VAR analysis, our first step was to determine the optimal number of lags for the time periods considered in our analysis. For the global financial crisis event study from 1/2007-1/2012 we obtained the following results using the AIC criterion, presented in table 2 below:

Table 2. Lag Selection: January 2007-January 2012

	Model (SPY and VVIX)	***Model (SPY and VIX)***
Lag	AIC	AIC
0	-9.66734	-9.14504
1	-9.64344	-9.12159
2	-9.64416	-9.10566
3	**-9.67792***	**-9.17328***
4	-9.66405	-9.16909

Our results for optimal lag selection indicate that a VAR model with 3 lags should be used for in our specification. Tables 3a and 3b highlight our results:

Table 3a. VAR Models: January 2007-January 2012 with VVIX
(Dependent Variable =SPY)

Lags	**Coefficient**	**S.E**	**z**	**p-value**
SPY1	0.0171	0.0492	0.35	0.728
SPY2	0.0475	0.0487	0.98	0.329
SPY3	0.1346	0.0445	3.02	0.003
VVIX1	0.0397	0.0161	2.47	**0.014****
VVIX2	0.0013	0.0155	0.08	0.934
VVIX3	0.0212	0.0173	1.22	0.223
Constant	-0.0005	0.0007	-0.72	0.470

Table 3b. VAR Models: January 2007-January 2012 with VIX
(Dependent Variable =SPY)

Lags	Coefficient	S.E	z	p-value
SPY1	-0.0410	0.0708	-0.58	0.563
SPY2	0.0519	0.0680	0.76	0.446
SPY3	0.2060	0.0593	3.47	0.001
VIX1	0.0016	0.0163	0.10	0.922
VIX2	0.0025	0.1472	0.17	0.865
VIX3	0.0293	0.0134	2.18	**0.029****
Constant	-0.0005	0.0007	-0.74	0.459

The results obtained indicate that there is a positive relationship between the VVIX measure and the SPY. The first lag of the VVIX is significant at the 5 percent level of significance in the model. The implication of these results for the specified time period is that an increase in the VVIX one period prior is positively related to movement in US equites as measured by the SPY. In the VIX model, the third lag is significant at the 5 percent level. The implications of these results for the specified time period are that uncertainty and volatility measures as proxied by the VVIX and VIX are positively related to increases in U.S. equity prices.

The last step in our analysis is to determine if our measures of uncertainty measures might be useful in helping to predict the U.S. stock market returns. We run a Granger causality test for our two VAR specifications and obtain the following results in Table 4. Our results indicate that VVIX can be used to predict SPY returns (5 percent level of significance), however the results for the VIX are not significant.

Table 4. Granger Causality Wald Test: January 2007-January 2012
(Dependent Variable = SPY)

Model (SPY and VVIX)		***Model (SPY and VIX)***	
Chi Squared	P	Chi Squared	P
8.0625	**.045** **	4.7708	0.189

The period spanning COVID presents an opportunity to study the US equity market during a time marked by high volatility and uncertainty. Following the same steps as outlined for the previous time period, we determine the optimal lag length and run our VAR model. Our results for optimal lag selection indicate that a VAR model with 1 lag should be used in our specification. Our results for the VAR can be found Tables 6a and 6b below:

Table 5. Lag Selection: June 2017-June 2022T

Lag	*Model (SPY and VVIX)* AIC	*Model (SPY and VIX)* AIC
0	-9.46613	-9.06813
1	**-9.65582***	**-9.13756***
2	-9.63259	-9.11529
3	-9.58955	-9.05583
4	-9.54172	-9.01983

Table 6a. VAR Models: June 2017-June 2022 with VVIX
(Dependent Variable =SPY)

Lags	Coefficient	S.E	z	p-value
SPY1	-0.2503	0.0353	-7.07	**0.000*****
VVIX1	-0.0321	0.0090	-3.58	**0.000*****
Constant	0.0007	0.0004	1.80	0.072

Table 6b. VAR Models: June 2017-June 2022 with VIX
(Dependent Variable =SPY)

Lags	Coefficient	S.E	z	p-value
SPY1	-0.2739	0.0427	-6.42	**0.000*****
VIX1	-0.0195	0.0064	-3.06	**0.002*****
Constant	0.0008	0.0004	2.06	0.040

The results obtained indicate that there is a negative relationship between the VVIX measure and the SPY as well as the VIX and the SPY. In both models, the first lagged variable is significant at the 1 percent level of significance. The relationship indicates that a decrease in uncertainty/volatility is related to an increase in U.S. equity returns as measured by the SPY. In our Granger causality analysis, presented below in Table 7, our results indicate that both the VVIX and VIX can be used as predictive variables in analyzing daily returns in the SPY ETF.

Table 7. Granger Causality Wald Test: June 2017-June 2022
(Dependent Variable = SPY)

Model (SPY and VVIX)		*Model (SPY and VIX)*	
Chi Squared	p	Chi Squared	p
12.795	**0.000 *****	9.3745	**0.002*****

The results indicate that in the first period (2007-2012), encompassing the global financial crisis, both the VIX and the VVIX are positively related to the SPY while in the second period (2017-2022) there is a negative relationship. A possible explanation for the differing effects of the VIX and VVIX on the SPY may be found in Table 1. If we look at the mean and standard deviation of daily changes of the VIX and the VVIX, we see that these statistical measures increased significantly in the second crisis period as compared to the first. When the mean and standard deviation of daily percentage changes of risk (VIX) and uncertainty (VVIX) are fairly low, the market sentiment may become more "risk-on", as in the first period, leading to a rise in the SPY and a positive relationship of VIX and VVIX with SPY. In contrast, in the second period the daily percentage changes in mean and standard deviation of both the VIX and the VVIX are much higher (38% and 43% for means and 31% and 20% for standard deviations for the VVIX and VIX respectively), leading to a change in market sentiment to "risk-off, resulting in a negative relationship of VIX and VVIX with SPY. Thus, whether risk and uncertainty are "connected" (i.e., they are both high or low) or "disconnected" (i.e., one is high and the other low) could explain the joint nature of risk and uncertainty in affecting market sentiment. The argument for uncertainty and risk becoming "disconnected" was raised by Ait-Sahalia, et al, (2021) who found that the equity premium is earned for facing uncertainty rather than risk.

SUMMARY AND CONCLUSIONS

In our VAR analysis of the how the VIX and the VVIX are related to U.S. equity prices, we obtain significant results for the two time periods examined, both periods of market turbulence. Our findings for the period during the global financial crisis indicate that an increase in our measures of risk and uncertainty is positively related to an increase in the SPY. Conversely, during the time period that spans COVID, we find the reverse holds true. These results appear to be a result of whether risk and uncertainty are "connected" or "disconnected"; that is their joint nature is what determines their effect on the equity market. These findings have implications for investment risk management. For example, if increases in both risk and uncertainty indicate a change in market sentiment to a "risk-off" attitude, the portfolio could be rebalanced toward fixed income or cash or hedging could be undertaken with put options or short positions. Reverse strategies would be employed if risk and uncertainty forecast an increase in market sentiment to "risk-on".

Future studies can focus on other measures of uncertainty, as well as forecasting models for equity markets that can potentially employ these variables. These potential proxies of uncertainty could also be employed in the analysis of other asset markets as well, such as the bond and currency markets. Additionally, more research is needed on the interaction between risk and uncertainty and their joint effects on asset markets.

REFERENCES

Azi, B., Cookson, J., and Izhakian, Y., 2022, Trading, Ambiguity and Information in the Options Market, SSRN: https://ssrn.com/abstract=4180712

Andersen, T., Fusari, N., and Todorov, V. 2020, The Pricing of Tail Risk and the Equity Premium: Evidence from International Options Markets, *Journal of Business Economics and Statistics,* 38(3), 662-678.

Asness, C., Moskowitz, T., and Pedersen, L., 2013, Value and momentum everywhere, *Journal of Finance,* 68, 929-985.

Bali, T., Brown, S. and Tang, Y., 2017, Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics,* 126(3), 471-489.

Bansal, R., Croce, M., Kiao, W., and Rosen, S., 2019, Uncertainty-Induced Reallocations and Growth, *NBER Working Paper No. w26248*

Ben-Rephael, A. and Izhakian, Y., 2020, Should I Stay or Should I Go? Trading Behavior Under Ambiguity, SSRN: https://ssrn.com/abstract=3628757

Brenner, M. and Izhakian, Y. 2018, Asset pricing and ambiguity: Empirical evidence, *Journal of Financial Economics,* 130(3), 503-531.

Brogaard, J. and Detzel, A., 2015, The Asset-Pricing Implications of Government Economic Policy Uncertainty, *Management Science,*61(1), 3-18.

Birru, J. and Young, T., 2020, Sentiment and Uncertainty, *Fisher College of Business Working Paper No. 2020-03-010, Ohio State University*

Cascaldi-Garcia, D. and eleven others, 2020, What is Certain about Uncertainty, *FRB International Finance Discussion Paper N. 1294,* The Federal Reserve System of The United States.

Chen, Z. and Epstein, L., 2002, Ambiguity, Risk, and Asset Returns, *Econometrica,* 70(4), 1403-1443.

Coiculescu, G., Izhakian, Y., and Ravid, S., 2019, Innovation under Ambiguity and Risk, *SSRN abstract=3428896.*

Daniel, K. and Hirshleifer, D. 2015, Overconfident Investors, Predictable Returns, and Excessive Trading, *Journal of Economic Perspectives,* 29(4), 61-88.

Dimmock, S., Kouwenberg, R., Mitchell, O., and Peijnenburg, 2016, Ambiguity aversion and household portfolio choice puzzles: Empirical evidence, *Journal of Financial Economics,* 119, 559-577.

Enke, B. and Graeber, T., 2020, Cognitive Uncertainty, *Technical Report,* National Bureau of Economic Research

Epstein, L. and Ji, S., 2014, Ambiguous volatility, possibility and utility in continuous Time, *Journal of Mathematical Economics,* 50, 269-282.

Epstein, L. and Schneider, M., 2008, Ambiguity, Information Quality, and Asset Pricing, *Journal of Finance,* 18(1), 197-228.

Epstein, L. and Schneider, M., 2010, Ambiguity and asset markets, *Annual Review of Financial Economics,* 2, 315-346.

Fama, E. and French, K. 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics,* 33, 3-56.

Fama, E. and French, K. 2015, A five-factor asset pricing model, *Journal of Financial Economics,* 116, 1-22.

Gennaioli, N., Shleifer, A. and Vishny, R., 2015, Neglected Risks: The Psychology of Financial Crises, *NBER Working Paper No. 20875.*

Izhakian, Y., 2017, A Theoretical Foundation of Ambiguity Measurement, *SSRN paper ID 724412*
.
Jegadeesh, N. and Titman, S., 1993, Returns to buying winners and selling losers; Implications for stock market efficiency, *Journal of Finance,* 48, 65-91.

Kahneman, D. and Tversky, A., 1972, Subjective probability: A judgement of representativeness, *Cognitive Psychology,* 3(3), 430-454.

Kozeniauskas, N., Orlik, A., and Veldkamp, L., 2018, What are Uncertainty Shocks?, *Journal of Monetary Economics,* 100, 1-15.

Markowitz, H., 1952, Portfolio Selection, *Journal of Finance,* 7(1), 77-91.

Mehra, R. and Prescott, E., 1985, The Equity Premium: A Puzzle, *Journal of Monetary Economics,* 15, 145-161.

Moreira, A. and Muir. T. (2017). Volatility-Managed Portfolios, *Journal of Finance,* 72(4), 1611-1644.

Moskowitz, T., Hua Ooi, Y, and Pedersen, L. 2012, Time series momentum, *Journal of Financial Economics,* 104, 228-250.

Nartea, G. and Bai, H., 2021, Investor Sentiment and the Economic Policy Uncertainty Premium, *Pacific Basin Journal of Finance (forthcoming).*

Pastor, L. and Veronesi, P., 2012, Uncertainty about Government Policy and Stock Prices, *Journal of Finance,* 67(1), 1219-1264.

Pastor, L. and Veronesi, P., 2013, Political uncertainty and risk premia, *Journal of Financial Economics,* 110(3), 520-545.

Routledge, B. and Zin, S., 2009, Model uncertainty and liquidity, *Review of Economic Dynamics,* 12(4), 543-566.

Tan, R., Manahov, V. and Thijssen, J., 2017, The Effect of Ambiquity on the UK Stock Market: Evidence from a New Empirical Approach, *Investment Management and Financial Innovations,* 14(4), 1-15.

The Economist, 2017, Are Traders Creating a Bizarre New Feedback Loop…Feedback Loop …Feedback Loop? April 7.