Determinants of Volatility: Calling It Quits on the VIX

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Determinants of Volatility: Calling it Quits on the VIX

A thesis presented

by

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to

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Abstract

This thesis explores the usage of the Chicago Board Options Exchange’s Volatility Index (VIX) in the current literature as a metric for broad investor sentiment and market volatility. The central premise of this paper is that the VIX has been taken out of context both by academics and practitioners in two distinct ways. Within academia, the VIX is used as a proxy for volatility across all asset classes even though implied and realized volatility in equities and fixed income are different. In practice, VIX-related products have been marketed as portfolio insurance products for a diverse investor base. The rise of leveraged ETFs that are pegged to the VIX futures curve instead of the VIX index lends itself to trading discrepancies given the information asymmetry between investors and the creators of these products. I also find that the introduction of these leveraged ETFs in the market is correlated to changes in the level of the VIX. I conclude that these two distortions of the uses of the VIX warrant a two-pronged response: a reexamination of the findings within the literature that are benchmarked to the VIX and a change in investor education with regards to VIX products.
Acknowledgements

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1 Introduction

Analyzing determinants of volatility within the markets continues to persist as a topic of interest for financial economists. Macroeconomic factors, regulatory frameworks, government policies, and the behaviors of financial institutions have all been examined as possible inputs into volatility. Not only does the current literature diverge in its stance on the effects of these individual characteristics, but it also leaves pockets of unexplained variation. What is particularly unique and true to volatility in the markets is the inability to come to a consensus about explanations for both bouts of increased volatility and periods of stability. Therefore, groups of economists and practitioners have taken their shots at modelling volatility to the best of their ability, in hopes of uncovering a trend in what would most accurately be described as a random walk.

The desire to develop a comprehensive model for volatility not only has its academic merits, but also potentially opens a Pandora’s Box of financial incentives. Market makers on the sell-side and investors on the buy-side thrive off of predictive knowledge - a surefire reason that billions of dollars have been poured into technological investments within finance. In an attempt at developing a model for stock market volatility, the Chicago Board Options Exchange (Cboe) did just that: by hiring one of the brightest minds in the field, Robert Whaley\textsuperscript{1}, they profited off their competitive

\textsuperscript{1}I had the pleasure of having a conversation with Robert Whaley, during which we spoke about his intentions for creating the index and discussed the results from his papers \textit{Understanding the VIX} and \textit{Trading Volatility: At What Cost?}. 

This paper takes a critical look at the use of the VIX in both academia and in financial markets. I argue that the VIX has been taken out of context both by academics and practitioners in two distinct ways. Within academia, the VIX is used as a proxy for volatility across all asset classes even though implied and realized volatility in equities and fixed income are different. In practice, VIX-related products have been marketed as portfolio insurance products for a diverse investor base. The rise of leveraged ETFs that are pegged to the VIX futures curve instead of the VIX index lends itself to trading discrepancies given the information asymmetry between investors and the creators of these products. I find evidence that there have been “wrong moves” in the VIX that are not explained by fundamental market moving events. I also find a positive relationship between ETF price and volume traded with the VIX level, and a negative relationship between return and the VIX level. As the level of the VIX trends up, the price and volume traded of these securities will also go up to meet the demand for this insurance. However, as the level of the VIX trends up, the return of these securities falls because of the futures curve contango trap. These two distortions of the usages of the VIX warrant a two-pronged response: a reexamination of the findings within the literature that are benchmarked to the VIX and a change in investor education with regards to VIX products.

I begin my analysis by providing a basic framework for the VIX index through introductions to the mechanics of equity options structures. I argue that the intended usage of the VIX is quite clear: to gauge investors’ propensities to purchase equity
index-based portfolio insurance. Instead, this message has been warped into a presentation of the VIX as a measurement of overall market volatility that can span asset classes. I explain this phenomenon within academia by isolating moments in the literature that use the VIX within inappropriate contexts. I demonstrate that academics defer to the VIX given the availability of data and information; furthermore, they justify their own usage by citing other literature that does the same thing. The cycle then perpetuates, and this index continues to persist without critical examination.

Regarding the contextual misplacement of the VIX, I first provide a theoretical motivation through Modern Portfolio Theory (MPT). My research demonstrates that one of the defining characteristics of MPT is a constant ratio of implied to realized volatility across asset classes. This motivation comes from the concept of the “rational investor.” By the tenets of MPT and behavioral finance, I argue that rational investors should diversify equally across all asset classes. If every investor follows this framework, then the ratio of implied volatility to realized volatility within all markets should be consistent with one another. A dive into the assumptions of this theory demonstrates that markets do not abide by these rules, making this characteristic invalid. I then move towards the empirical research and show how implied and realized volatility differ by asset class. Finally, I review major movements in the VIX, revealing by “proof of existence” that there are inherent flaws in the predictive mechanism of the VIX.

I then shift gears to discuss the other side of this argument within the leveraged ETF space. Given the asymmetry of information that exists with these products due
to their inherent complexity, investors find themselves pouring money into products that they do not fully understand. The mandates of pension funds and endowments limit their ability to make investments in futures and options, thereby pushing these funds towards VIX exchange-traded products (ETPs). These VIX ETPs are based on the VIX futures curve, which is a very different exposure profile to trading the VIX index. I then explore the relationship between leveraged ETFs and the VIX using data on 237 ETFs from 1990-2018. I find a significant negative relationship between the level of the VIX and average quarterly return, and a significant positive relationship between average quarterly price and average quarterly volume traded.

To further motivate our findings, I dive into the interconnectedness of the equities markets to the fixed income markets. Movements within these two asset classes are correlated with one another. Equity products often have baskets of underlying securities that are derivations of fixed income products. Interest rates, which are the fundamental inputs when determining the price of a bond, impact stocks in a whole host of ways. Individual companies can be impacted greatly by interest rate movements, particularly when considering capital structure and interest payments to debt holders. These payments impact bottom-line earnings, and can determine the amount of return that will be extended to equity holders in dividends. These relationships all factor into the market value of a company’s equity, causing movements in the stock markets. Therefore, these macroeconomic indicators that impact the fixed income markets also drive volatility within equities. These synergies between equity and fixed income markets lends itself to an environment where portfolio managers and
investors seek a variety of different risk-reward strategies that span multiple asset
classes. Some investors look for yield, while others look for steady cash flows. Some
require hedging tools, while others look for leverage. The wide diversity of strategies
opens up endless possibilities for portfolio construction.

In constructing their portfolios, investors and consumers of volatility-driven prod-
ucts have taken the accepted measurements and indices of volatility as givens in the
products they purchase and the continuing research that is being produced. Industry-
wide inertia coupled with a lack of a better measurement tool for volatility resulted
in the perpetuation of the VIX throughout the literature. Given that this index has
earned considerable clout within the world of finance, this standardization in the
literature has encouraged academics to defer to using the VIX without much justi-
fication. However, it is important to note that groups of practitioners are aware of
the inadequacy of these existing tools but fail to make this asymmetry of information
known.

With this brief introduction into the landscape of volatility, it becomes clear that
a critical examination of our measurements for volatility is crucial for not only the
academic literature, but also for the private sector. The VIX is currently the bench-
mark that is used throughout academia to describe volatility in the markets, and the
literature often spends little to no time discussing the merits or concerns with using
this index. Therefore, as I demonstrate in the following analysis, the literature that
makes use of the VIX as a benchmark for volatility must be reexamined to clarify the
underlying motivation for the utilization of the index.
A critique of the VIX is the key to bridging the gap between proprietary models for volatility and publicly-marketed ones. Firms within the financial services industry are in the business of understanding volatility and using that knowledge to both further their own bottom-line interests and those of their clients. Therefore, the lucrative opportunities that exist when these firms generate accurate models for volatility should give us pause in contextualizing the motivations for marketing volatility products. This call for a reexamination is particularly pressing given the ever-changing landscape of financial markets, as innovation explodes within the field and new products challenge the current frameworks of volatility.

My contribution to the literature is to demonstrate that a formal critique of the VIX has not been performed to date. I find that there is no simple solution to this issue of contextual misplacement given the widespread use of the VIX, but it must begin with extensive investor education. The significant amount of capital invested in VIX ETPs where investors are unclear about the underlying assets they are investing in appears particularly worrying and warrants further research.
2 Literature Review

2.1 Background on the VIX

This section provides the reader with the necessary toolkit for evaluating the uses of the VIX in academia and in practice. By exploring both the mathematical formulation for the VIX options basket and the structure of the VIX futures curve, I demonstrate the limitations of the predictive power of this index and the products that are derived from the futures curve. This information will provide the reader with a backdrop for the impending discussion about the misuse of the VIX in academic literature. To further motivate the empirical discussion, I argue that the shape of the VIX futures curve demonstrates the mean-reverting tendency of the VIX and relays information about potential market sell-offs and rallies. Understanding whether the curve is in contango or backwardated is a key component to the VIX ETP market. A volatility curve that is in contango is pricing in a volatility expansion in the future where longer-dated contracts become more expensive. A volatility curve that is in backwardation is pricing in a volatility contraction in the future where longer-dated contracts become cheaper. This market is derived off the movements of the VIX futures curve - when the curve is in contango, the returns on these products trend towards zero. As I will discuss further, this contango trap must be well understood before investors purchase these securities.

In 1993, the Chicago Board Options Exchange Global Markets, Incorporated (Cboe) introduced the Cboe Volatility Index (VIX) as a new method to measure
the 30-day volatility of at-the-money S&P 100 Index option prices. The VIX measures near-term investor sentiments about the markets, and is colloquially referred to as the “fear gauge”. In 2003, Goldman Sachs and Cboe decided to update the volatility metric to best reflect expected volatility in the US markets. They decided to use the S&P 500 Index (SPX) as the new benchmark index, whereby they aggregate a variety of SPX puts and calls to create the VIX. By using SPX options with more than 23 days and less than 37 days to expiration, the index always represents the interpolation of two points along the S&P 500 volatility term structure (Cboe VIX White Paper 2018).

The quoting convention for the VIX is important to understand given that it does not reflect a “price”. The VIX is quoted as a percentage, and estimates an annualized standard deviation. For a VIX level of 16, investors expect the S&P 500 to move 16% over the next year with a probability of 68% (the probability of a one standard deviation move).

The VIX was intended to provide investors with a metric for short-term market volatility. A few years before the creation of the VIX, the markets had recently experienced the crash of October 1987, which was the greatest disturbance the markets had seen since the Great Depression. To quantify the magnitude of the effect on the markets from these events, financial engineers looked towards options pricing models to determine a basket of puts and calls that would provide information on forward-looking volatility.

Furthermore, the product was intended to be used as a way for investors to bet
on volatility. Just as investors take bets on stocks and bonds, there was increasing demand in the investor population to express views on volatility in the markets. Therefore, an entirely new market of futures and options opened up with the introduction of the VIX that had previously been unimaginable. As these products emerged, the VIX began to be used as a diversification product for investors who were looking to strengthen the performance of their portfolios. Given relevant data concerning volatility and market returns, investors wanted to mitigate the negative correlation that existed within their portfolios in the event that the stock market experienced bouts of great volatility.

The calculation of the VIX can be likened to the relationship of a bond’s yield to maturity and the price of the bond (Whaley 2009). The yield is implied within the price of the bond because investors are estimating how much of the cash flows are going to be returned to them. Similarly, Whaley (2009) writes that the VIX uses the bid/ask spread of options to determine the implied VIX level, where the options on the S&P 500 are measuring expected volatility over the next 30 days.

When it was first introduced in 1993, the VIX utilized option prices of the S&P 100 Index. At the time, the most actively traded options market were those on the S&P 100. Therefore, when the creators of the VIX looked to build their volatility index, they wanted access to the most liquid and active options markets. The original VIX was based off eight at-the-money (ATM) calls and puts. Given that ATM calls and puts were the most widely traded at the time, these options contained the largest amount of speculative activity (Whaley 2009).
To further our mechanical understanding of the VIX, it is imperative to examine the composition of the puts and calls that make up the generalized VIX calculation.

The following formula is the generalized VIX calculation:

\[
\sigma^2 = \frac{2}{T} \sum \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T} \left[ \frac{F}{K_0} - 1 \right]^2
\]

Where:

\[
\sigma = \frac{VIX}{100}
\]

\[
T = \text{time to expiration}
\]

\[
F = \text{forward index level derived from index options prices}
\]

\[
K_0 = \text{First strike below the forward index level, F}
\]

\[
K_i = \text{Strike price of } i^{th} \text{ out-of-the-money option; a call if } K_i > K_0 \text{ and a put if } K_i < K_0; \text{ both put and call if } K_i = K_0
\]

\[
\Delta K_i = \text{interval between strike prices – half the difference between the strike on either side of } K_i
\]

\[
\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}
\]

\[
R = \text{risk-free interest rate to expiration}
\]

\[
Q(K_i) = \text{the midpoint of the bid-ask spread for each option with strike } K_i
\]

From the equation, we can see that when \( K_i < K_0 \), it is a put option. This means that if we have investors buying more puts, then the value of \( \frac{1}{T} \left[ \frac{F}{K_0} - 1 \right]^2 \) becomes less than the value of \( \frac{2}{T} \sum \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) \), thereby pushing the value of the VIX upwards.

When \( K_i > K_0 \), the reverse is true, so when we have more call options the level of the VIX is pulled down.
However, once the S&P 500 (SPX) became more popularized and began to attract attention within the options space, the creators of the index decided to base the calculations off S&P 500 options. As the options markets within SPX became more active, there was a shift towards out-of-the-money options and away from at-the-money options. Whaley (2009) writes that this shift can be attributed to the fact that out-of-the-money put options are essentially insurance contracts for the option buyer. Put options give the option buyer the right to sell an asset for a specified price at an agreed upon date in the future. Alternatively, calls give the option buyer the right to buy an asset for a specified price at an agreed upon date in the future. Therefore, using put options as insurance for trades within a portfolio during turbulent market environments became the trend. The revised VIX also added a variety of new put and call option combinations, making the index much more robust given that it is less sensitive to the movements in a particular option’s price. Therefore, the mechanics of the VIX are as follows: when investors buy more calls than puts on the S&P 500, the VIX trends downwards, reflecting positive sentiments within the markets. When investors buy more puts on the S&P 500, then the VIX trends higher to reflect increasing uncertainty and fear in the markets. The majority of investors who buy options on the S&P 500 are looking to hedge their fears of potential stock market volatility, causing them to purchase puts for their portfolios. Whaley (2009) describes this as “portfolio insurance” on the market, where the price of the VIX correlates to the price of buying insurance on the market at any given point (pg. 100).

An examination of the VIX futures curve gives us some fundamental insights into
the ways in which volatility responds to investor sentiments and its mean-reverting property: when the VIX spikes or falls below its normal levels, it always returns to its equilibrium value. VIX futures markets provide us with information about expectations for future volatility, whereby the price of future VIX contracts can help investors predict whether the market is expecting a sell-off or a rally. As demonstrated in Figure 1\textsuperscript{2}, the VIX futures curve starting with contracts from March 2019 is in contango.

![VIX Futures Term Structure](vixcentral.com)

**Figure 1: VIX Futures Curve**

When a futures curve is said to be in "contango", it means later-dated futures contracts are priced at a premium to shorter-dated contracts. Therefore, a contango VIX futures curve means that the price of buying insurance on the markets is increasing over time. This means that the outlook for the markets in the next several months is slightly pessimistic, whereby investors are predicting a sell-off in the markets.

\textsuperscript{2}Source: CBOE Delayed Quotes (vixcentral.com)
The switch between backwardated and contango volatility curves in anticipation of market sell-offs and rallies demonstrates the mean-reverting tendency of volatility and the VIX. This can be shown by the following thought exercise: on average, the stock market tends to trend upward. The average percentage of “up days” in the stock market is around 53% - this evidence is further supported by the fact that there is a positive drift component in the Geometric Brownian Motion that models stock price movements within the Black-Scholes Model, demonstrating that prices tend to drift higher (Guntar et al 1999). Given that there is an inverse relationship between price and volatility, it should correspond to a contracting volatility environment.

As mentioned above, a volatility curve that is in contango is pricing in a volatility expansion in the future where longer-dated contracts become more expensive. To confirm that volatility is mean-reverting, the VIX futures curve must enter into a state of backwardation. A backwardated VIX futures curve has shorter-dated contracts priced at a premium to longer-dated contracts. The curve is pricing in a volatility contraction - this typically occurs after a sell-off in the markets when investors start to regain confidence in the markets.

Based off the structure of the VIX and the VIX futures curve, the analysis now moves toward a deep dive into the academic literature. In the next section, I explore the uses of the VIX index within a variety of contexts, whereby a fundamental grasp of the concepts presented above is necessary in evaluating the efficacy of these claims.
2.2 Usages of the VIX in the Existing Literature

The motivation for this section is to understand the contexts in which the VIX has been used within academia. I argue that the empirical research surrounding the VIX falls into two groups, both of which are concerned with misusing the VIX in extraneous contexts. These discussions hearken back to my central thesis, which looks to determine these contextual misplacements in both the academic literature and empirical applications. One group of literature utilizes the VIX as a proxy for volatility across all asset classes and fails to provide any meaningful justification for this implementation other than the fact that other papers have also done this. The second group of literature focuses on the misunderstanding amongst investors about the construction of VIX ETPs given the divergence between the VIX futures curve and the index. I conclude this section by determining that VIX products are a way for profit-maximizing firms to market a new product set and capitalize off the asymmetric information barrier between practitioners and investors.

An examination of the results that have been derived from the VIX demonstrate that academia has taken this index for granted and has used it as its benchmark for overall market volatility throughout the literature. The ease of acquiring data on this index as well as the fear of creating a sub-par measure for volatility has contributed to this misappropriation of the VIX as a benchmark for volatility outside the equity markets.

The proliferation of the usage of the terms “fear gauge” and “measure of investor
sentiment” are rampant throughout the literature. The marketing of the VIX as a measure for volatility outside the equity markets, and specifically outside the S&P 500, accounts for the somewhat reckless usage of this product without proper qualifications. Citing other literature that uses the VIX as a volatility proxy should not be a reason to use this index freely and without any premeditation. However, that is exactly what has occurred, as demonstrated in an example by Chung and Chuwonganant (2017). They confirm their methodology by citing previous examples of papers whose topics vary significantly in breadth and scope. The only similarity that these papers have is their need for a measurement for volatility. Even a quick glance at the papers that have been cited demonstrates the persistence of this index throughout the literature.

Fernandes, Medeiros, and Scharth (2014) look to develop an understanding of the time-series characteristics of the VIX index. Like many before them, they begin by outlining that the consensus understanding amongst academicians is that the VIX is “the barometer of the overall market sentiment as to what concerns investors’ risk appetite” (pg.1). The paper fails to specify the constraints of this index’s predictive power, thereby generating further misconceptions about the ability of this index to reflect investor sentiment outside the equity markets. Ivan Oscar Asensio (2013) emphasizes the widespread reach of this index both in the literature and in practice. He writes, “The VIX has been embraced as a risk management vehicle by investors, a barometer for risk aversion by financial markets participants, and an input to econometric specifications and robustness tests by academic researchers.”
Asensio (2013) writes about the difficulty surrounding trading the VIX basket, whereby traders opt to purchase VIX futures contracts instead of the basket itself to gain exposure to market volatility.

This practical component related to trading the VIX further exacerbates the complexity of the relationship between the theoretical implications of the VIX and the practical uses. Asensio (2013) finds that “Ex ante forecasts of future changes in the level of the VIX, implied by the VIX term structure, overshoot ex post changes, especially over shorter tenors” (pg.1). As mentioned in the motivations for this section, Asensio argues that this divergence between the VIX futures curve, where traders can express their views on volatility, has grown with the influx of capital from both retail and institutional investors and the emergence of exchange-traded funds. The evidence that the VIX futures curve overshoots the measured implied volatility of the VIX index provides further impetus for a critical examination of the products that are derived from the VIX futures curve, such as VIX ETPs. Furthermore, using futures and indexes interchangeably reveals a fundamental educational concern that has driven a wedge between practitioners and academics. Problems arise when all these measures are conflated into one term deemed “volatility”.

Another example of this phenomenon playing out is documented within the corporate bond market. Bao, Pan, and Wang (2011) use the VIX to capture “overall market conditions” within the fixed income markets, thereby making their analysis contingent on the idea that changes in the VIX models movements in corporate bond market volatility accurately (pg.5). In a similar vein to the analysis of Bao et al., Pan
and Zeng’s (2017) analysis rests on the idea that increased volatility reduces ETF arbitrage, which is generated by pricing discrepancies between the underlying basket of bonds and the actual ETFs. The writers acknowledge that an ideal measure for market volatility within the corporate bond ETF market is not the VIX (Pan et al. 2017). They write “Ideally, we would like to use a counterpart of the VIX in the corporate bond market. A counterpart does exist in the government bond market: the Merrill Lynch Option Volatility Estimate (MOVE) Index is a yield curve-weighted index of the normalized implied volatility on 1-month Treasury options which are weighted on the 2, 5, 10, and 30 year contracts.” (pg.26). They argue that there is a 0.76 correlation between this index and the VIX, but do not specify why they failed to use the more accurate metric. Similarly to the papers above, they justify their usage by citing additional papers that also opt into the VIX (Pan et al. 2017).

The divergence in the motivations and technical usage of this index drives the variability in interpretations of volatility. Traders who are looking to add volatility exposure to their portfolios cannot directly express their views via the VIX index. The tools at their disposal are VIX futures, options, and exchange-traded products (these are securities that are traded on exchanges with underlying assets related to the VIX). Trading the VIX options basket can be technically challenging, given the unique construction and weightings of this basket. If replicated, it will not necessarily yield the same results and can produce materially different results from the VIX for some investors.

To ensure stable exposures to the movements of the VIX, VIX ETPs were mar-
marketed to both retail and institutional investors whose mandates do not allow for trading within the futures and options markets (Whaley 2013). These products aim to mimic the movements of the VIX, but depending on liquidity constraints and rebalances, they can veer off course. VIX ETFs should only be used for short-term hedging since their rebalancing costs and inherent structural problems do not make them accurate insurance measure for longer time periods. Many VIX ETPs missed expected returns by a large margin during the February 2018 market correction due to these fundamental shortcomings (Whaley 2013).

Given that volatility trading has gained traction throughout the portfolios of certain institutional and retail investors, there are varying levels of complexity in the products that are marketed to different individuals. These products are accompanied by 300-page prospectuses written in dense legalese that only lawyers and specific product specialists can appropriately parse through (Whaley 2013). The motivation for this index was much more than just developing an accurate metric for stock market volatility. It was a way for the Cboe to create an entirely new set of financial derivatives that relied on the VIX as its underlying asset. As volatility trading became more popular, the Cboe was looking to capitalize off investor interests by giving them exactly what they wanted: an easy way to add volatility hedging to their portfolios. This is the fundamental trap - retail clients think these products are related to the VIX index, and they think they are investing in the movements of the actual VIX index. In fact, they are taking bets on the VIX futures curve, whose contango quality ensures that the expected value of these products held for long periods of
time is zero. Whaley (2013) stated that since the VIX itself has an upward bias, the curve is primarily in contango. This “contango trap” pushes VIX futures prices down towards the index level. Given the complicated construction of these futures products, the profits are cut into by rebalancing fees, management costs, and other exchange-traded product expenses (Whaley 2013).

Theoretical recommendations as demonstrated in academia often cannot be replicated in practical contexts given these trading constraints. These discrepancies are not noted in the current literature given the variability of situational contexts that could pertain to individual traders. Furthermore, it is in the best interest of the Cboe to deemphasize the difficulty of trading this index and the complexity of the financial derivatives related to the VIX. The literature fails to take these constraints into account, thereby further bolstering our hypothesis about inappropriate uses of this index. Not only does academia employ this index outside of its intended scope throughout theoretical research contexts, but also traders and investors have deployed capital into an idea that does not technically allow for direct investment. Therefore, the observed movements in the VIX are a combination of technical results and, as Whaley (2009) describes it, portfolio insurance. To further motivate our results, I now transition to a discussion about theoretical motivations for our main hypothesis.
3 Problems with the VIX

3.1 Theoretical Motivations: Modern Portfolio Theory

The previous sections demonstrated the extent of the two-pronged problems that are a result of misuses of the VIX. To motivate my findings, I first provide a theoretical overview of the key components of Modern Portfolio Theory (MPT). I find that in a market where the laws of MPT are obeyed, the ratio of implied to realized volatility across asset classes should be fairly similar. However, the blatant violations of the assumptions of MPT within the markets demonstrates that the theory does not hold. Therefore, conflating the uses of the VIX and extending it to both the equities and fixed income markets is not supported by the the findings of MPT. Furthermore, I move on to provide empirical examples of these violations. The first empirical section examines the realized and implied volatility within equity and bond markets and compares the data, finding that Fed policy has been the primary driver for this differentiation. Furthermore, I isolate movements in the VIX and divide them into four scenarios to showcase flaws in its predictive measures. By “proof of existence”, I show that not only are the applications of this index misplaced, but the index itself also fails in its mandate to be a holistic measure of market volatility.

Modern Portfolio Theory, developed by Harry Markowitz in 1952, looks to explain the ways in which rational investors approach the process of portfolio construction (Markowitz 1952). Based on this theory, the rational investor looks to gain the highest amount of yield, or reward, for the lowest amount of risk through portfolio
diversification. By selecting different proportions of securities within the portfolio based on their payout profile, the rational investor can essentially complete a simple optimization problem to maximize expected return. In the case that an investor is presented two portfolios with exactly the same return profile, they should end up choosing the less risky of the two. The investor should only seek more risk in return for higher reward (Markowitz 1952).

The theory assumes that asset returns are normally distributed random variables, which is far from the reality of the return profiles of any asset. Moreover, it assumes that investors are rational and are consciously aiming to maximize return over all else. It does not account for investors who are aiming for a particular level of risk, which is particularly relevant for individuals with retirement and savings funds. Another key element of MPT is the assumption that all investors have the same sources of information about investment decisions. The existence of asymmetric information within the markets is a crucial component to the inherent inefficiencies that exist within the markets. Information advantages are what sell-side and buy-side firms compete for, whether that be in acquiring top talent or developing the most efficient technological systems. Furthermore, the theory assumes that individual investors are not large enough to influence price fluctuations. The presence of major behemoth investment banks, hedge funds, mutual funds, and private equity firms immediately discredits that assumption. Should these funds release their holdings into the market all at once, the market would completely change. Therefore, these funds rely on a variety of stealthy methods to decrease their footprint on technical price movements.
(Markowitz 1952).

As demonstrated by the list of assumptions above, the shortcomings of this theory within the real world become relevant. The assumption of the rational investor who is looking to optimize his portfolio in one particular reward-maximizing method does not describe the vastly diverse set of investors who participate within the markets. The discrepancy between the assumptions of MPT and reality have been widely explored in the field of behavioral finance, which looks to provide a theoretical framework for these differences. Behavioral economists look towards psychology to be able to explain deviations within the stock market that are outside the realm of typical movements. Not only does this field operate under the assumption that investors are often irrational, but it also argues that the results of this irrationality are expressed in market outcomes. Ultimately, the key to these theories is that the investors and market participants that are responsible for volatility in the markets are humans with inherent biases. The inclination to act a certain way due to personal reasons outside the realm of rationality cause individuals to act in ways that are not explained by MPT. When these types of behaviors occur all throughout the markets, as they do in the real world, then the markets are subject to inefficiencies. These inefficiencies manifest themselves in asset bubbles, price corrections, and periods of excessive euphoria or fear within the markets.

Operating under the assumptions of MPT, the rational investor would have no preference investing in a debt or equity product (Markowitz 1952). As I discussed in the introduction of this section, the question of preferences becomes more relevant
to our understanding of the VIX. In our conception of the world that includes irrational investors, this diversification strategy seems unlikely to apply to all market participants. Some investors will look to invest only in equities, while others look specifically to fixed income. Therefore, the risk-return profiles of these portfolios will all vary based on the priorities of the individual investors. Given this uneven balancing between different asset classes, the implied and realized volatility metrics within equities and fixed income cannot be proportional to one another. If they are not proportional to one another, then the use of the VIX to describe broad market sentiments about volatility becomes questionable. However, the current literature surrounding market volatility relies on this assumption of rationality. The translation into real world markets does not carry over, and acknowledging this discrepancy is the first step in identifying the mismatch between the perceptions of volatility as presented by academia and those that come from observing trends within the markets.

Interestingly, measurements for implied volatility within the fixed income markets do exist. These relatively unpopular metrics are also products marketed by the Cboe, and are derivations of the VIX index. These include products like the Cboe Interest Rate Swap Volatility Index (SRVIX) and the Cboe/CBOT 10-year U.S. Treasury Note Volatility Index (TYVIX). The SRVIX measures market volatility within the interest rate swap market, which was the first standardized measurement for fixed income implied volatility. The TYVIX was the first model-free volatility index on US government debt. These metrics were designed as a way to provide investors access to fixed income volatility trading, just as the VIX index had done in the equity space.
These indexes appear sparsely in the empirical finance literature. A small number of authors cite the existence of these fixed income volatility indexes, but go on to use the VIX instead as their proxy of volatility for research within the fixed income markets. They cite availability of data on the VIX as being the primary source for use of the VIX equity index, but this substitute would only be valid if the relationship between implied and realized volatility were constant between asset classes. As I outlined above, that is one of the assumptions of MPT and rational investor behavior. However, these assumptions are continuously violated in the markets.

A vital component of MPT is that investors do not have liquidity constraints and are able to purchase the exact securities they want to express their positions (Markowitz 1952). However, the reality of investing as a retail client as opposed to an institutional investor demonstrates the power of money in these systems: money gives you access, and access gives you information. That information is ultimately what drives investors’ decisions about portfolio construction. It is also particularly useful in evaluating the efficacy of VIX-related ETFs. The primary discussion about these products lies in understanding the difference between the VIX index itself and the VIX futures curve. Given that investors do not have access to the same levels of information, these discrepancies run rampant in investment decisions (Whaley 2013). Therefore, this theoretical motivation demonstrates the inadequacy of the real world markets to live up to the assumptions of MPT. By using the VIX as a proxy for volatility across all asset classes, it unintentionally assumes that these assumptions are not violated in the markets. In the next section, I lay out exactly how these
implied and realized volatilities differ from one another and why these proxies are not always appropriate in the empirical data.
3.2 Empirical Observations: Volatility by Asset Class

The empirical applications of our discussion presented above demonstrate the differences between equity and fixed income volatility. Historically, the volatility in one market would trigger volatility in the other. This section challenges this assumption and demonstrates that historical perceptions of volatility are changing given new Fed policies and the entrance of more sophisticated financial derivatives within the markets. These differences are evident in the changes in the relationship between the VIX and short-term treasury yields due to the Fed’s decision to reverse quantitative easing. Furthermore, the introduction of leveraged ETFs and VIX ETPs that are derived from the VIX futures curve presents another dilemma. Futures curves allow investors to gain a sense for the price of insurance in a particular market in the future. I find that the VIX futures curve and the Treasury Volatility Index Futures (TYVIX) Curve do not always present the same picture of their respective markets. Based off the differences between the contango and backwardated structures, I demonstrate an example where the VIX futures curve predicts a rally with less overall market volatility, whereas the TYVIX futures curve predicts a sell-off with more overall market volatility.

As demonstrated by Figure 2, the last 10 years showcases a fairly well-correlated relationship between equity and fixed income volatility. When equity market volatility would spike, the stock market would sell off. Investors would move their assets into safe haven assets like government bonds, knowing that their capital would be pro-
protected by these “riskless” assets. Therefore, their losses would be somewhat hedged by their fixed income positions. However, as demonstrated in Figure 3 on the next page, this correlative relationship has begun to change. US treasuries, which typically rally when stocks fall, are no longer reacting in the short term.

The trend lines in Figure 3 demonstrate the change in the magnitude of the movements between the VIX and short-term treasuries. The volatility skyrocketed in the VIX through 2017 and 2018, where the movements were completely out-sized as compared to the past several years.

As I mentioned above, there are two major reasons that these dynamics have changed over the past decade, and they are both connected to the Fed’s decision to end its term of quantitative easing: an increase in the supply of treasuries and increased number of rate hikes.

After the financial crisis, central banks turned towards quantitative easing as
a way to relieve the markets of stress and encourage consumer confidence. The government served as the guarantor for trillions of dollars worth of debt, which they did by repurchasing government securities. This capital influx into the economy enabled investor confidence and stimulated the markets to the point where Fed officials thought it was time to reverse their policies. As the Fed began its quantitative tightening regime, the government debt that they had been buying became available to other market participants. The new buyers of this debt are less forgiving then the Fed, and are more attuned to price movements (Gorodnichenko and Coibion 2016). Not only did these yield-seeking investors fixate on price, but they also did not jump at the possibility of owning debt with low or negative real yields. With this change of buyers and the increase in supply of these securities due to rising fiscal debt via tax
cuts and government spending, the traditional supply/demand forces are no longer at play. There is no anxiety in the markets that there will not be enough of these safe haven assets, leading to a less reactive bond market (Gorodnichenko et al. 2016).

Given that short-term rate levels rely primarily on Fed policy, changes in overnight bank funding rates lead to movements in short-term treasury yields. Rate hikes most directly impact these short-term securities, which makes the supply and demand of these products reliant on the Fed’s hiking plan. As an investor looking to gain exposure to risk-free securities during a hiking cycle, it would make more sense to invest in longer-dated treasuries given that the Fed has continued to articulate their desire for more rate hikes in the short-term. This type of attitudinal shift has led to differences in bond market and equity market volatility. This particular correlative change is extremely important given the proxies that many academics use in modeling fixed income volatility in the bond markets. Most of the papers justified their usage of the VIX by citing historical correlations between the liquidity within these markets and volatility in the equity markets as modeled by the VIX.

To examine this phenomenon, I will take a look at realized volatility in equity markets and bond markets in 2018. Data from Bloomberg and III Capital Management shows the following graph in Figure 4:

As we can see from Figure 4, the difference in volatility between the equity markets and bond markets is stark: the realized volatility on the S&P 500 rose by 357% over

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3This section utilizes data from https://www.forbes.com/sites/garthfriesen/2018/04/08/the-death-of-bond-market-volatility/cea57d166748. I use the image in Figure 4 and certain data values.

4Source: Bloomberg and III Capital Management
the course of 2018, whereas investment-grade bond market volatility rose by 14%.

Stock market realized volatility normally averages around 12%, whereas bond market realized volatility normally averages around 2.8%.

Within the US, increased threats for trade wars have rocked the equity markets. Although the macro environment should impact fixed income markets as well, the flight to safety has kept bond volatility at much more reasonable levels. The driver for these differences in volatility means that either the equity markets will work through the technical correction and revert back to less volatile intraday moves, or the fixed income markets will need to readjust to the current market setting (Engle, Ghysels, and Sohn 2013).

These differences in bond market and equity market volatility are mirrored in the futures market. As I explored earlier, these markets move between backwardation and contango. The shape of the futures curve provides investors with a gauge for expected future volatility and the price for insurance in the future.
In Cboe’s data, they release information about futures curves for both the TYVIX (the treasury volatility index) and the VIX. As demonstrated in Figure 5, a striking juxtaposition of these two curves demonstrates the divergence in implied volatility predictions for these two asset classes in 2016.

Figure 5: VIX futures in Backwardation and TYVIX futures in Contango

The VIX futures in Figure 5\textsuperscript{5} are in backwardation, singling a drop in volatility premiums. This downward sloping curve means that VIX futures are predicting a rally in the equity markets with less overall market volatility. However, TYVIX futures are in contango, signaling a rise in the volatility premium for treasuries. The upward sloping curve means that TYVIX futures are predicting increased levels of volatility and a potential sell off, which showcases the differences between the volatility

\textsuperscript{5}Source: Cboe Blogs: Twists and Turns In VIX and TYVIX Indexes (Shalen 2016)
expectations in these markets.

Just as the futures curve of VIX and TYVIX reveal different perceptions of volatility between asset classes that question the use of the VIX, I look to further motivate the empirical findings by presenting inherent flaws in the predictive power of the VIX in the next section.
3.3 Empirical Observations: Movements in the VIX

The purpose of the analysis in this section is to provide another layer of analysis to the inherent flaws of this index. I identify four scenarios of predictive ability for the VIX, and argue that by virtue of the existence of examples within each of these groups, the VIX does not properly capture overall market volatility.

Figure 6: Graph of the VIX from Inception

Figure 6 shows the VIX index since its inception. To begin to dissect these movements over the past 26 years, I have isolated points in the history of the VIX to examine. To gain a sense for whether the VIX is an appropriate measure of market volatility, there are four scenarios that I can examine in this event analysis:

- Option 1: There is a market-moving event in the markets that is noticed by investors, and the VIX predicts it.

- Option 2: There is a market-moving event in the markets that is not noticed by investors, and the VIX predicts it.
- Option 3: There is a market-moving event in the markets that is noted by investors, but the VIX does not predict it.

- Option 4: A market-moving event does not occur, but the VIX moves.

I comb through news events for each of the significant days to identify whether there were market-moving events. By examining Wall Street journal articles, New York Times articles, and various miscellaneous news outlets, I identify both macro and equity market news to see if the movements in the VIX are technically or fundamentally driven. As I will demonstrate, events that fall within the last two categories signify a flaw in the VIX index’s predictive ability. Options 1 and 2 show that the VIX works, so I will lump those together in my explanation. Isolating the analysis into the four categories aids in showcasing that the VIX is not a holistic gauge of volatility in the markets across all asset classes.

**Options 1 and 2**

Option 1 demonstrates the scenario where market-moving events are noticed by investors, and the VIX predicts them. The most salient examples of this scenario are major macro market events that end up being widely publicized in the news. The sub-prime mortgage crisis is one example of an event that was talked about for many months as the housing bubble began to grow. The VIX slowly spiked up throughout 2007 and early 2008, until it spiked to its highest levels to date in late 2008 with the crash of the stock market. The financial crisis was anticipated by investors,
particularly those who were involved with the mortgage-backed securities markets.

Another example of this type of predictive behavior was during the Greek Debt Crisis. Investors were acutely aware of the increasing amount of debt that Greece had accumulated. After the financial crisis, a combination of austerity and structurally inefficient monetary policy measures created one of the most prolonged financial crises that the Western world had experienced. In the lead-up to the crisis, the VIX slowly began to rise as investors feared that the weakening Greek economy would impact other Western countries.

Option 2 is one of the more difficult scenarios to isolate. However, the VIX has a few moments where it has predicted a volatile event before investors caught wind of the trend.

April 2010 is one example of this behavior. The VIX levels start to rise even though fundamentals are relatively sound. On April 12, 2010, the Dow closes above 11,000 for the first time in 18 months. Furthermore, Europe begins to loan money to Greece in an effort to quell any uncertainty about their economic instability. Although these measures were put in place, the VIX continues to climb throughout April and into May. By the end of May 2010, VIX levels trend around 40, as political tensions have fully surfaced with regards to the European debt crisis. The Euro slumps as a result, and this sends markets into turmoil. The weakening European economies led to a strengthening of the dollar against the Euro, thereby hurting American exports.

These fears had gone unnoticed within domestic markets since investors had assumed that the EU would take care of the Greek debt issue without much fuss.
However, the size of the problem escalated over the course of the month, and the VIX levels demonstrated this uncertainty.

**Option 3**

Unlike options 1 and 2, the presence of options 3 and 4 reveals inherent flaws in the VIX’s predictive ability. Option 3 demonstrates a scenario where investors notice a market-moving event, but the VIX does not react.

An example of this type of event occurred in July 1994. The markets were experiencing a particularly weak retail cycle, with investors aware of decreased amounts of consumer spending. When consumers taper their spending habits, it signals an economic movement towards slower growth. This type of behavior should generate a movement in the VIX, as it has at other points of economic slowdowns (like the European debt crisis or the Asian financial crisis). Throughout the entirety of that month, the VIX did not spike above 12 or 13, even though the retail sector experienced two straight months of declining sales and lagging economic growth.

**Option 4**

The final option showcases a scenario where there is no relevant market-moving news, but the VIX moves. Traders typically call these technical moves in the VIX, and these movements occur without a fundamental market-moving event. This type of move can occur in the VIX regardless of whether there is actually additional volatility being generated in the markets.
Two examples of technical movements in the VIX were the stock market crash of 1987 and the February 2018 XIV (the inverse VIX exchange-traded note) bubble. Although the VIX was developed in 1993, the creators of the VIX calculated historical levels prior to its inception. In 1987, the stock market experienced a huge sell-off that impacted global markets. Sell orders flooded traders’ screens, and the DOW lost 22% of its value. These losses were driven by a global financial meltdown as a bear cycle began to overcome the markets.

However, these losses were exacerbated by technical program trading issues. The VIX skyrocketed due to the malfunction of program trading systems. These systems would liquidate holdings once they reached a certain stop loss limit. As the markets tanked, these trading systems triggered a series of stop losses and began flooding the markets with increased supply. This influx of shares drove prices down, causing the VIX to spike to a level of 60. These levels were completely unprecedented and quickly recovered as these program trading systems were taken under control.

These types of technical movements remained a part of the life of the VIX. In February 2018, the VIX surged by 115%, hitting levels of 40. This was caused by a huge sell-off in XIV. This exchange-traded note provides investors with inverse exposure to the VIX. When speaking to Whaley about this particular move, he highlighted this moment as a technical move caused by the unknown power of VIX-related ETPs. The collapse of XIV was a purely trading related maneuver which triggered a huge spike in the VIX.

Through a combination of theoretical motivations and empirical analysis, I have
showcased the first portion of my analysis about the misuse of the VIX. The use of the VIX as a proxy for volatility across all asset classes is not justified by theory or empirical analysis. Now, I shift towards the second misuse of this index: the rise of leveraged ETF products that are pegged to the VIX futures curve instead of the VIX, thereby completely altering the exposure profiles of these assets.
4 Leveraged ETF Data Analysis

4.1 Analysis of Leveraged Exchange-Traded Funds

The motivation for the following sections is to build out the analysis for the second core argument of this thesis, which showcases another situation where the VIX has been taken out of context. The rise of leveraged ETFs that are pegged to the VIX futures curve instead of the VIX index lends itself to trading discrepancies given the information asymmetry between investors and the creators of these products. I also find that the introduction of these leveraged ETFs in the market is correlated to changes in the level of the VIX. One possible explanation for this correlation is the path dependency characteristic of these ETFs, whereby there is an exaggerated effect on the volatility of the underlying index and individual assets. I conclude that these distortions of the uses of the VIX warrant a change in investor education with regards to VIX products. To start off, I dive into an overview of the ETF market as a backdrop for the impending discussion.

Over the past two decades, the presence of exchange-traded funds within the markets has flourished and continues to grow. These products, first created as simple index-tracking instruments for a relatively small investor base, have grown into some of the most sought-after products on the market. Market activity during the financial crisis spurred a movement toward passive investing, making these products extremely attractive to investors who were looking to strengthen returns in their portfolios via index-tracking products. Global ETF assets have grown from $417 billion in 2005
to $4.4 trillion at the end of September 2017. This is a cumulative average growth rate (CAGR) of 21%. The growth of ETFs over the past decade has surpassed the expectation of financial innovators, who argue that these instruments are one of the single most important innovations to enter the market. The global macroeconomic environment has worked in favor of these assets and has placed emphasis on the following shifts: self-directed retirement savings, low yields, digital distribution, and passive investing. Estimates for growth into 2020 place the global asset value at $7.6 trillion (EY Global ETF Research 2017).

In the 1990s, the first ETFs were purely designed to track specific equity indexes and provide steady returns to their investors. As the market began to become saturated in these initial ETF products, providers began to expand the offerings they could generate for their clients. This included expansion into fixed income, commodities, currencies, and leveraged ETFs. The popularity of these products can be attributed to a variety of causes, some of which are tax efficiency, low expense ratios, and cost transparency. This extension into new underlying assets has caused great variation within trading styles, costs, and management fees for ETFs across the board. ETFs vary in their bid/ask spreads, particularly for those with lower liquidity. Based off empirical data, leveraged ETFs are more frequently traded than their non-levered peers (Cheng et al. 2009).

Three major characteristics of ETFs have attracted the attention of researchers within the field of financial innovation: pricing discrepancies between the ETF and the underlying asset, the performance of ETFs, and effects of ETF trading on related
securities or indexes. Pricing discrepancies between ETFs and their underlying assets have presented unique arbitrage opportunities for ETF traders. The creation and redemption process used to create ETFs generates an arbitrage opportunity between market prices and their relative net asset values (NAVs) (Charaput et al. 2012). Depending on the ETF, these purchases and sales can either be done in-kind (using a basket of the underlying securities) or in-cash. For example, if the market price of an ETF is below its value, the trader can buy units of the ETF in the market and redeem them for the underlying basket of securities, thereby locking in the price differential. Studies on ETF pricing demonstrate that ETFs generally trade at a premium or discount to their NAVs. For most ETFs that track large equity indices, this premium/discount has been arbitraged out of the price. This discussion of pricing efficiency sets up the analysis for pricing leveraged ETFs, which are a class of ETFs that return a multiple of the daily returns of the particular index or basket of securities (Charaput et al. 2012).

The purpose of leveraged ETFs is to provide a multiple of the exposure on a particular index or basket of securities. These funds use financial derivatives and debt to construct funds that will provide a specified level of return. These products were first introduced into the market in 2006 and immediately took off due to the demand that existed for this type of instrument.

To construct a leveraged ETF, the fund will employ a variety of futures contracts, forwards contracts, and total return swaps. This impacts the way that these funds are able to partake in the creation/redemption process since they can only pursue in-cash
instead of in-kind. Charupat and Miu (2012) determine that the price deviations are, on average, small and within bid/ask spreads. What is unique to leveraged ETFs are the patterns that Charaput and Miu (2012) find within the price deviations. Bull funds trade at a discount to bear funds, and bull funds have negatively correlated returns with their underlying indices while bear funds react in reverse. They find that these price deviations are a result of the adjustments that are made within the basket at the end of the trading day to maintain leverage ratios.

For example, when an index exhibits positive return at the end of the trading day, the issuers and swap counterparties of both the bull and bear funds increase their exposures of the index by buying more of the underlying securities. The compression of these trades at the end of the trading day creates a larger rebalancing demand, thereby generating price volatility and contributing to movements in price in the underlying securities. This effect is exaggerated for indices where the aggregated assets under management (AUM) of the leveraged ETFs that are tracking them are more extensive. Ben-David, Franzoni, and Moussawi (2014) argue that there is evidence to suggest that there is exogeneous variation within the daily volatility of stocks owned by ETFs that can attributed to ETF ownership. They use non-levered US ETFs for their analysis, and find that an increase in one standard deviation in ETF ownership correlates to a 16% increase in daily stock volatility. Therefore, they conclude that the ETF arbitrage contributes to volatility in the trading patterns of the underlying securities (Ben-David et al. 2014).

There are several reasons why these products were able to capture a previously
untapped demand in the markets. Leveraged ETFs enable hedge fund investors and traders the ability to put a directional play on the books that spans a variety of sectors and asset classes. What would have before been a complicated basket trade executed by an investment bank could now be accomplished by purchasing a single leveraged ETF. This newfound ease feeds into the second reason that investors became automatically attracted to this space. Leveraged ETFs were now another way to put leverage on a portfolio without having to purchase a variety of complex financial derivatives such as swaps, options, and futures. Since ETFs are managed by a particular issuer, the purchaser of the ETF does not have to actively manage the derivative exposures and no longer has to trade around options expiry. Investors not only freed up capital but also human resources when they transitioned over to using ETFs. Once portfolio managers realized this simplicity and convenience, they began to express long-term leveraged directional bets using leveraged ETFs and hedged their portfolios in the process. Certain institutional investors, like pension funds and endowments, were limited in their mandates to trade directly within the futures and options markets. These products enabled these investors access to a completely new market (Whaley 2013).

Given the immensely innovative nature of these products, researchers have made it a priority to study the overarching impacts of the trading patterns of these products on the market as a whole. A unique characteristic of leveraged ETFs is the need to rebalance them at the end of each trading day. Although it seems obvious, it is important to note that the rebalancing activity is directionally the same as the
movements of the underlying assets in that day (Cheng et al. 2009). However, what
is not obvious is the way in which long and short hedging positions counteract the
rebalancing effects. The trading flows from leveraged ETFs that take the long and
short positions in equivalent underliers do not counteract one another. In fact, the
impact is related to the assets of the ETFs, the leverage multiple, and the returns of
the underlying assets. Cheng and Madhavan (2009) provide an illuminating example
of the phenomenon described above. They demonstrate that a double-inverse ETF
promising -2x the index would necessitate putting on a hedge that returns 6x the
fund’s daily NAV whereas a regular double-leveraged ETF would only require 2x the
return. This path dependency is crucial given the exaggerated effect on the volatility
of the underlying index and individual assets Cheng et al. 2009).

These rebalancing demands have sparked research in the volatility of these assets
at the close of the trading day. Given that traders must rebalance based on the day’s
closing return values, it would be expected to see the greatest amount of market
activity right around the close. Cheng and Madhavan (2009) confirm this finding by
performing a linear regression analysis on the closing volatility, where they determine
that the statistical significance of the regression coefficient reveals greater amounts
of volatility at the close.

The existing literature on ETFs and volatility instruments continues to broaden
as these relatively recent financial innovations are becoming the subject of rigorous
research. Frijns, Tourani-Rad, and Webb (2016) describe how investment banks cre-
ated a variety of products to circumvent the complexity of trading these assets. One
of the initial reactions to address this market deficiency was to introduce a product called “variance swaps”. These swaps allowed investors to express directional views on volatility in the markets, but were operationally intensive for investment banks to buy and sell contracts. To make these contracts more accessible to different types of investors, funds created ETFs that track volatility measurements and could be easily traded. Once this product was introduced into the market, investors latched on at the opportunity of taking positions on volatility in the market (Frijns et al. 2016).

Given the introduction of volatility ETFs and leveraged ETFs, the question of liquidity for esoteric underlying assets became the subject of further research. In their paper, Kevin Pan and Yao Zeng (2017) look to provide a theoretical understanding to the unique problem of liquidity mismatches in corporate bond ETF data and how this can create significant market inefficiencies. ETFs often track non-equity underliers, which means that the OTC contracts that they trade can have unique settlement terms and inventory risks that exchange-traded underliers do not have. Therefore, if this discrepancy exists in the liquidity of the underlying asset and the ETF, there are potential arbitrage opportunities that can be exploited and can lead to general market fragility. The opposition to this theory argues that the abundance of these products in the market at large should quell the impacts of this liquidity mismatch; however, Pan and Zeng (2017) argue that for a subset of esoteric ETFs with extremely illiquid underliers, this hypothesis does not hold.

On the subject of volatility instruments that track leverage, Nina Boyarchenko (2018) looks to understand the deviations from parity of asset prices in basis trades
in a variety of asset classes. They argue that the current understanding in finance is that no matter how an asset provides exposure to a particular kind of risk, there should not be a difference in price. However, the impact of regulation and the increased cost of participation creates these limited arbitrage opportunities. This directly relates to the idea of directional volatility trades in ETFs creating these liquidity mismatches.

The data, which comes from Morningstar, contains information on the ETF’s fund manager, yield, market price, category, average daily volume, and the legal structure of the fund. The data set also includes the “Global Category”, which essentially describes the types of assets that are being tracked by each ETF. This is incredibly important as it distinguishes those ETFs that are tracking equities versus fixed income products and will isolate those that are volatility-tracking ETFs as opposed to those that are not.

The overarching data set is comprised of 2,248 ETFs that are all traded on US exchanges, of which there are 16 true volatility ETFs and 237 levered ETFs. The volatility ETFs fall within the larger subset of levered ETFs. The data spans 1990-2018.

I examined daily price, daily volume, yearly return, net income ratio, net assets, shares outstanding, net expense ratio, monthly return, and daily tracking volatility (a measure of the random variation in a fund portfolio versus its benchmark index) for the volatility ETFs and leveraged ETFs.

The following tables showcases quarterly averages across return, price, and volume for the leveraged ETFs. This gives us a time series data set from 1990-2018.
Table 1: Summary Statistics for Average Return, Average Price, and Average Volume

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Pctl(75)</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return (in %)</td>
<td>61</td>
<td>1.136</td>
<td>4.754</td>
<td>-13.711</td>
<td>-1.249</td>
<td>2.625</td>
<td>13.207</td>
</tr>
<tr>
<td>Price (in $)</td>
<td>61</td>
<td>90.783</td>
<td>58.597</td>
<td>32.773</td>
<td>44.282</td>
<td>124.133</td>
<td>226.379</td>
</tr>
<tr>
<td>Volume (in shares)</td>
<td>61</td>
<td>2,402,123</td>
<td>3,475,604</td>
<td>19,009.09</td>
<td>556,615.4</td>
<td>2,866,528</td>
<td>16,592,677</td>
</tr>
</tbody>
</table>

The statistics from both Table 1 and 2 showcase the salient points about this data set. Table 2 reveals this information in more granularity. The average monthly return on these leveraged ETFs is around -0.151%, where the middle 50% fall between -4.5% and 4%. There is a slight negative bias to these ETFs, but on the whole they average out close to 0% return. However, there is an interesting phenomenon when it comes to Yearly Returns. The average there is around 3%. This can be explained by the upward bias of the markets. On smaller time frames, this bias is less present given there are more volatile intraday moves. However, over the year, there is a slight positive bias.

Another noteworthy point within this data set is the amount of volume traded within these names. Table 1 provides this as quarterly information, and Table 2 has the daily averages. The amount of volume traded in these names gives us a sense for how much capital is flowing through these products and gives us a sense for the size of the market.
<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Standard Deviation</th>
<th>Max</th>
<th>Min</th>
<th>p25</th>
<th>p75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Tracking Volatility</td>
<td>2.421</td>
<td>3.768</td>
<td>19.995</td>
<td>0.004</td>
<td>0.178</td>
<td>2.488</td>
</tr>
<tr>
<td>Monthly Return</td>
<td>-0.151</td>
<td>11.732</td>
<td>169.926</td>
<td>-69.302</td>
<td>-4.467</td>
<td>4.005</td>
</tr>
<tr>
<td>Net Expense Ratio</td>
<td>0.764</td>
<td>0.529</td>
<td>10.57</td>
<td>0</td>
<td>0.58</td>
<td>0.95</td>
</tr>
<tr>
<td>Daily Price</td>
<td>43.889</td>
<td>33.475</td>
<td>552.739</td>
<td>2.094</td>
<td>23.601</td>
<td>54.326</td>
</tr>
<tr>
<td>Yearly Return</td>
<td>3.622</td>
<td>41.319</td>
<td>270.430</td>
<td>-97.609</td>
<td>-23.794</td>
<td>19.725</td>
</tr>
<tr>
<td>Net Income Ratio</td>
<td>0.813</td>
<td>1.717</td>
<td>6.03</td>
<td>-10.5</td>
<td>-0.850</td>
<td>1.760</td>
</tr>
<tr>
<td>Daily Portfolio Concentration</td>
<td>4.427</td>
<td>2.758</td>
<td>9.995</td>
<td>0.188</td>
<td>2.273</td>
<td>6.329</td>
</tr>
<tr>
<td>Net Assets</td>
<td>323,289,735</td>
<td>926,922,610</td>
<td>9,980,344,940</td>
<td>0</td>
<td>10,926,603</td>
<td>271,276,946</td>
</tr>
<tr>
<td>Shares Outstanding</td>
<td>6,967,696</td>
<td>16,048,647</td>
<td>119,598,980</td>
<td>3,900</td>
<td>350,000</td>
<td>9,089,884</td>
</tr>
<tr>
<td>Daily Volume</td>
<td>843,110.8</td>
<td>3,104,946</td>
<td>172,569,130</td>
<td>0</td>
<td>1,133</td>
<td>190,571</td>
</tr>
</tbody>
</table>
The graph of average return for leveraged ETFs in Figure 7 reveals their mean-reverting quality. The return oscillates dramatically for the first several years, making out-sized returns during the late 1990s and losing steam throughout the early 2000s. The past several years have seen returns hovering around zero. Based off the relationship between these products and volatility, I argue the following: as these products mature and become more heavily traded in the markets as buy-and-hold investments, the supply and demand dynamics pull these products toward zero return. This is a product of low volatility environments within the markets that make investments within leveraged ETFs less attractive. Instead, investors use these as portfolio insurance products. However, the design of these products is such that they trend towards zero return if held over long periods of time.
To gain a better sense for the relationship of leveraged ETFs to the level of the VIX, I regress average quarterly volume, price, and quarterly returns. This allows us to understand the relationship between the introduction of these assets into the market and the subsequent levels of the VIX. Not only do these products generate out-sized levels of volatility due to their construction, but this regression will identify the aspect of these ETFs that is related to the VIX level. The regression equation that I use to analyze the data is the following:

\[ VIX_t = \alpha + \beta_1 Volume_t + \beta_2 Price_t + \beta_3 Return_t + \epsilon_t \]

The main coefficient of interest is \( \beta_3 \), which shows the relationship between the return on leveraged ETFs and the level of the VIX. This coefficient provides us with understanding about the volatility feedback loop between these assets and the VIX. \( \beta_2 \) demonstrates the relationship between the price of these assets and the level of the VIX. Since price and return are also correlated with one another, these variables synergistically contribute to movements in the VIX.

Table 3 contains the regression output where each of the variables is regressed individually with the level of the VIX. Table 4 regresses volume and return, price and return, and then all three variables together. I choose return as the one variable that should consistently remain in the regressions since it is the coefficient of interest. Therefore, I look to examine the relationships between return and the other variables in the regression.
Table 3: Results

<table>
<thead>
<tr>
<th>Dependent variable: VIX Level</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Quarterly Volume</td>
<td>0.021***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Quarterly Price</td>
<td></td>
<td>0.075***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Average Quarterly Returns</td>
<td></td>
<td></td>
<td>-0.766***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.200)</td>
</tr>
<tr>
<td>Constant</td>
<td>13.333***</td>
<td>11.536***</td>
<td>19.228***</td>
</tr>
<tr>
<td></td>
<td>(0.578)</td>
<td>(1.641)</td>
<td>(0.968)</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>61</td>
<td>61</td>
</tr>
<tr>
<td>R²</td>
<td>0.806</td>
<td>0.404</td>
<td>0.808</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.799</td>
<td>0.383</td>
<td>0.798</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>3.648 (df = 58)</td>
<td>6.398 (df = 58)</td>
<td>3.660 (df = 57)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>120.607*** (df = 2; 58)</td>
<td>19.644*** (df = 2; 58)</td>
<td>80.097*** (df = 3; 57)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Table 4: Results

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX Level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Average Quarterly Returns</td>
<td>-0.086</td>
<td>-0.587***</td>
<td>-0.088</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.178)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>Average Quarterly Volume</td>
<td>0.020***</td>
<td></td>
<td>0.019***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Average Quarterly Price</td>
<td></td>
<td>0.064***</td>
<td>0.016*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.014)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Constant</td>
<td>13.560***</td>
<td>13.174***</td>
<td>12.450***</td>
</tr>
<tr>
<td></td>
<td>(0.653)</td>
<td>(1.599)</td>
<td>(0.917)</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>61</td>
<td>61</td>
</tr>
<tr>
<td>R²</td>
<td>0.806</td>
<td>0.404</td>
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<td>80.097*** (df = 3; 57)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
The first set of regressions reveals a variety of relationships between these variables and the level of the VIX. The coefficients of volume traded and price are positively correlated with the level of the VIX, while return is negatively correlated. This makes sense in the context of supply and demand relationships. VIX products are more in demand when there is volatility in the markets since they are used as portfolio insurance to mitigate against large swings in the market. As the level of the VIX trends up, the price of these securities will also go up to meet the demand for this insurance. Furthermore, the volume traded increases when these securities are in higher demand. However, as the level of the VIX trends up, the return of these securities falls because of the contango trap. Since these products are not pegged to the level of the VIX but are instead pegged to the VIX futures curve, their returns are pushed to zero.

The second set of regressions reveals the associations between these variables. Although the directionality of these variables do not change, thereby showcasing that the interpretation remains the same, the magnitude of the effect is slightly altered. The coefficient on returns becomes slightly more negative, and the coefficients on volume and price become slightly less positive. The negative correlation between return drags down the other two variables by a small margin. However, the interpretation of the regression does not change.

In the following section, I delve into the mechanics of the contango trap that has driven the results of these regressions.
4.2 VIX Exchange-Traded Products

Given my findings about the relationship between the levels of the VIX and leveraged ETFs, I use this section to focus specifically on VIX ETPs. I demonstrate the major information asymmetry that has generated another rift in market perceptions about these products. I argue that it is in the best interest of firms who are in the business of marketing these products to maintain this asymmetry given that investors are pouring their money into bespoke products for which they will pay a premium.

As I mentioned in the previous sections, the extension of ETFs to the VIX allowed both retail and institutional investors the opportunity to enter the volatility trading world. Whaley (2013) explains the attraction that these VIX ETPs have for uninformed investors. The trend has grown to the point that there are now 30 VIX ETPs with a market value of $4 billion, generating $800 million worth of trading volume. Whaley (2013) argues that these investments are not suitable buy-and-hold investments, which questions the ability of investors to actively participate in trading volatility in the markets. Furthermore, the efficacy of the results from academic research is limited to a niche group of investors (Whaley 2013).

In their prospectus about VelocityShares (a VIX ETP), Credit Suisse AG writes (Whaley 2013), “The long term expected value of your ETNs is zero. If you hold your ETNs as a long-term investment, it is likely that you will lose all or a substantial portion of your investment.” (pg.1) This is because of the VIX contango trap, which I alluded to in the explanations of the VIX futures curve. Given that retail investors,
pension funds, and endowments are restricted in their futures and options trading, these products provide an outlet for investors who are looking for volatility exposure in their portfolios. However, given that they are not actually buying into the index itself, the volatility they are investing in triggers losses in the market that generate volatility feedback loops. The investors who are looking for exposure to volatility buy into the VIX at a certain point, but the futures curve pulls their investments to zero (Whaley 2013). When investors lose money and panic in the markets, they pull their capital - this triggers increased levels in the VIX. Increased VIX levels attract a new round of volatility-hungry investors, thereby perpetuating the cycle of volatility. Therefore, as these products become more prevalent within the markets, they start to generate artificial volatility. This form of volatility is not based on fundamental moves within the equity and fixed income markets: it is instead a byproduct of misunderstood futures markets where investors are unequipped to ascertain the difference between volatility product offerings.

The Cboe’s aim is to capitalize off their index, and these products are the ultimate bait. Paradoxically, the index which people want to invest in benefits off the purchases of securities that are not pegged to the actual index itself. Through the analysis from this section, I conclude the following: by generating more volatility in the markets, this index becomes more desirable to investors, and they flock to VIX ETPs as the easiest exposure method.
5 Conclusion

This paper explored the use of the VIX index throughout the academic literature and evaluates its practical context amongst retail and institutional clients. I first showcase the complacency within academia in choosing a volatility index. The literature relies on this index given the fear of the lack of the better metric, and does not make adjustments to correct for the faulty assumptions. I use Modern Portfolio Theory as well as themes from behavioral finance literature to showcase these assumptions.

To fully understand the volatility within this index, I compare realized volatility and implied volatility within the equity and fixed income markets. By analyzing historical trends and examining the VIX and TYVIX futures curves, I conclude that the relationship between implied and realized volatility within the fixed income and equity markets does not match. Therefore, substituting the VIX as a benchmark for volatility in a setting that looks to evaluate both fixed income and equity securities fails to account for the nuances that are inherent in these markets.

I then identify notable movements in the VIX to assess its predictive power. By identifying four scenarios of market news interacting with investor sentiment and movements in the VIX, I reveal the shortcomings in the ability of the VIX to reflect investor sentiment. Particularly, the technical movements within the VIX are a key aspect of the unexplained variation that feeds into determinants of volatility.

In an effort to further analyze the technical gyrations in the VIX, I look towards VIX ETPs. These products exacerbate the divergence between access to volatility
instruments between retail and institutional clients. These products not only operate under misconstrued assumptions, but they also feed into the volatility loop that is generated when investors indirectly trade the VIX futures curve as opposed to the index. This evidence is supported by the regression analysis that I conduct, which demonstrates that there are significant relationships between price, volume traded, and return of leveraged ETFs and the level of the VIX.

My contribution to the literature is to demonstrate that a formal critique of the VIX has not been performed to date. This accepted metric of volatility has contributed greatly to advancements in understanding volatility, but the contexts in which it is employed must be reexamined to ensure that it is not extending beyond its original intention. Given that I find that there is contextual misuse of the VIX both in academia and in the financial markets, I conclude that there is no easy solution to rectify this mismatch. A cultural shift towards the colloquial usage of this index is necessary, and must begin with extensive investor education. Furthermore, the trends within the VIX ETF market are particularly worrying. The fact that there is a significant amount of capital invested in products where investors are unclear about the underlying assets seems to eerily parallel the lead-up to the financial crisis of 2008. Although I am by no means suggesting or predicting a particular fate for this market, I believe that there is merit in exercising caution with regards to these investments.

The complexity of the volatility machine drives this research and reveals the intricacy of the financial markets. Determinants of volatility change as the financial
markets change, and it is our job to continue to adjust our models and assumptions
to fit this ever-changing landscape.
6 References


