

# Recent Volatility in U.S. Equity Markets: A Review of Key Contributing Factors and Relationships

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## ABSTRACT

*This paper is a review of volatility trends, factors, and relationships in U.S. equity markets, with emphasis on the period of time from 1980 to the present, when volatility has been at higher levels than what had been observed earlier. Both finance academics and investment professionals are affected by this 'high-volatility' environment, as it impacts the traditional relationships that connect risk and return, and can therefore alter both individual asset and portfolio allocation decisions. Based on a thorough review of the literature on a stock's idiosyncratic volatility, we explain why it has increased in recent times, discuss factors that affect volatility level, and provide an overview of the empirical relationship between current volatility levels and future expected return. At the end of each section, we pose a related idea for future research – there are ten such ideas offered. The primary purposes of the paper are to convince the reader that volatility is an important investment consideration, to identify the major findings in recent volatility research, and to highlight some unanswered volatility questions for future academics and practitioners to explore.*

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## INTRODUCTION: VOLATILITY DEFINITIONS AND TRENDS

In an equity portfolio, investors should care about more than just the returns on each of their individual stocks. More specifically, they should also worry about the volatility of each individual stock, as given by idiosyncratic, or firm-specific, volatility, since shifts in these levels may cause a previously diversified portfolio to become much less diversified. Although investors can eliminate idiosyncratic volatility by holding a fully-diversified portfolio, many investors choose not to hold well-diversified portfolios. For such investors, if the volatility for some portion of their individual stocks increases, they will need to add more stocks to their portfolio in order to achieve the same level of diversification, which will result in higher transaction costs (Xu & Malkiel, 2003). Because investors require higher returns to invest in firms with larger idiosyncratic volatility (in order to compensate for the loss of diversification), there may be a positive link between idiosyncratic volatility and the cross-section of expected returns (Bali & Cakici, 2008).

Furthermore, both abnormal event-related returns and stock prices in general depend on firm-specific volatility, industry-level volatility, and market volatility (Campbell, et al., 2001). The finance literature is clear in establishing links between idiosyncratic risk and subsequent returns, although less clear about the direction of this relationship. Volatility also serves as a proxy for the divergence of opinion in the market (Guo & Savickas, 2006), and therefore, may affect the behavior of option traders and arbitrageurs, whose profits and hedging strategies will be impacted by how quickly prices change over a given time period. Financial markets often overreact to idiosyncratic risk in the short-term, relative to what firm fundamentals may indicate.

The most well-known measure of volatility in U.S. markets is the VIX, which represents the implied volatility of a synthetic at-the-money option on the S&P 500 index that has a time to maturity of one month. Here, the term 'implied volatility' refers to a specific volatility level for the option's underlying asset (e.g. – a stock) that would produce the observed option price in the market. In contrast, 'historical volatility' looks at some arbitrarily long past period of time, and measures the standard deviation of daily price changes (or the log of daily price changes) over that period. If one uses historical volatility to estimate current or future volatility levels, it is implicitly, and often erroneously, assumed that past volatility trends will continue into the future. Because the VIX, commonly known as the 'fear index,' is known to have very high serial correlation (Ang, et al., 2006), the uncertainty of returns can be forecasted more readily than the absolute level of returns itself. Market crashes tend to occur during periods of high sentiment (i.e. – when VIX is high), although the exact timing of these crashes is nearly impossible to predict (Baker & Wurgler, 2007).

Volatility measures for asset prices can cover a wide variety of time frequencies. Choices include daily, monthly, quarterly, annual, or even longer periods. Jones and Wilson (2004) examine data from 1871-2000, and use 26 non-overlapping 5-year periods, with 60 monthly observations for each of the 26 five-year periods. The three highest volatility sub-periods for stocks occurred from 1931-1935, 1936-1940, and 1926-1930, respectively. Officer (1973) found that the variability of market returns declined between 1926 and 1960 due to the formation of the SEC in 1933, the institution of margin requirements in 1934, and a larger number of stocks being listed on the NYSE (so that the market itself became more diversified). He also cited 1942 as the year when market volatility 'returned to the normalcy' that existed before the Great Depression. From 1940-1999, Jones and Wilson (2004) showed that individual stock volatilities remained relatively level, except for the 1986-1990 period, which was higher almost exclusively due to the October 1987 crash. They also found that, after adjusting for inflation, stock volatilities were about 3 times higher than bond volatilities. However, in the last half of the 20th century, the relative risk of stocks compared to that of bonds declined dramatically (since bond volatility has been increasing faster than stock volatility). Although there is a positive relationship between current volatility and subsequent returns for bonds, this relationship can be negative for stocks.

The VIX was high during the turbulent period from 2000-2002, low during the calm period of 2003-2006, and high again during the financial crisis of 2007-2009. When cross-sectional volatility, which measures the dispersion of stock returns within an index at a single sub-period in time, is low, like it was from 2003-2006, there are fewer opportunities for portfolio managers to earn superior alpha relative to their peers. However, when cross-sectional volatility is high, as it was from 1998-2002 or 2007-2009, the range between good and bad investments will widen. Note that, although the market decline in the recent financial crisis began in October 2007 (the month of the all-time DJIA peak), it took almost a full year for volatility levels to really kick in.

The initial primary driver for the sudden rise in volatility was increasing energy costs, which ate into corporate earnings and created much future uncertainty. Then, in 2008, when Bear Sterns and Lehman Brothers collapsed, volatility levels continued their dramatic ascent, and persisted at alarmingly high levels due to fundamental problems within the financial services industry. In 2010-2011, the VIX fell from its financial crisis peak levels, although it was still quite high, but in 2012, it receded even further back to normal levels (Bouchey, 2010). This is surprising, since many analysts circa 2010-2011 were predicting the high-volatility environment to continue for several more years due to severe structural problems within the U.S. and other major world economies (Darnell, 2009).

In addition, U.S. stocks have been significantly more volatile than non-U.S. stocks. From 1990-2006, Bartram, Brown, and Stulz (2012) found that the stocks of U.S. firms were more volatile than comparable foreign firms across almost all years in the sample. They introduce two types of volatility: 'good' and 'bad,' and attribute the volatility advantage more toward the good kind. 'Good volatility' has been higher in the U.S. due to greater investor protection and stock market development, and more new patents and firm investment in research and development. Thus, individual U.S. firms may have been more innovative, and exemplified higher risk taking and entrepreneurship levels than their foreign peers. Meanwhile, non-U.S. firms have been exposed more to 'bad volatility,' which includes political risk and other country-specific forces that individual firms cannot control. These forces tend to prevent growth and productivity, and foster an environment of instability and higher noise trading. A related trend is that while U.S. stocks have exhibited higher firm-specific volatility, foreign firms have been exposed to greater systematic risk (Bartram et al., 2012).

The main body of this article is organized as shown in the following table:

No.	Section Title	Primary Question of Interest
1	Idiosyncratic Volatility	What are the various types of idiosyncratic volatility, and how are idiosyncratic volatility levels estimated?
2	Explanations for Volatility Trending Upward	Why has idiosyncratic volatility shown a general upward trend over the past 50 years?
3	Determinants of Cross-Sectional Volatility	Which factors have been linked to both idiosyncratic and market volatility levels?
4	The Relationship Between Return and Volatility	What is the direction of the relationship between volatility and future return levels, and why is there such disagreement in the literature about this link?
5	Factor Models for Explaining Excess Return	Which factors have been linked to excess return, and how does this relate to idiosyncratic volatility levels?
6	The Momentum Anomaly	What is the momentum anomaly, and how does this relate to idiosyncratic volatility levels?
7	Investor Sentiment	How does investor sentiment contribute to extreme market volatility?
8	Examples of Extreme Volatility Events	What constitutes an 'extreme volatility event,' and what are some recent examples of such events?
9	Managing Liquidity Amid Extreme Volatility	When extreme volatility has been present, how has the market attempted to avoid a liquidity crisis?
10	Managing Volatility with Derivatives	How have call options, put options, and combined option strategies been utilized to manage volatility?

We also provide an idea for future volatility research (*in italics*), at the end of each upcoming section, along with corresponding implications for investment practitioners. In addition, we conclude with a summary that reviews the primary purposes for this paper and its most

essential findings, and an inventory of remaining future research areas that will help enable both investors and academicians to better understand volatility.

At this point, and throughout the majority of the upcoming discussion on volatility, the focus turns exclusively to one specific type of volatility: 'idiosyncratic,' or firm-specific volatility.

## **IDIOSYNCRATIC VOLATILITY**

The primary measure of volatility in the finance literature is 'idiosyncratic volatility (IV),' which isolates the price risk for an individual firm. Since a particular stock's IV is not directly observable, it can only be estimated. Xu and Malkiel (2003) identify two differing approaches to estimating IV: the direct method and the indirect method. The direct method uses residuals from a factor model for excess returns, and defines IV to be the standard deviation of these residuals, so that aggregate IV (across all stocks) would be the weighted sum of these variances, where the weights are the market capitalizations of each stock. The indirect method considers the difference between the weighted sum of the variance of stock returns (in excess of the risk-free rate) and the variance of market returns (also in excess of the risk-free rate).

Arena et al. (2008) employ an alternative to the direct method, and calculate IV using residuals from a 2-factor model, where the factors are the market return and the market return 1-day earlier (so as to account for the effects of non-synchronous trading). They also reference 'FF IV,' or Fama-and-French Idiosyncratic Volatility (Fama & French, 1993),' which uses residuals from a 3-factor (size, value, and market return) model. Brandt et al. (2010) calculate IV-like measures for each stock, each industry, and for each time period in their study, where all are based on the residuals between an individual stock return and its corresponding industry return, which are then aggregated upwards across industries and time periods. Chua et al. (2010) start with the 3-factor Fama-and-French model, but then decompose IV into expected IV (EIV) and unexpected IV (UIV). Here, after defining IV to be the sum of squared residuals from the factor model (across all days in a particular month), the EIV is formed using an AR(2) time series model, which relies on IV measures from the previous 2 months. Then, the UIV is simply the difference between IV and EIV for a particular month. The purpose of UIV is to control for variation in unexpected returns, so that the true connection between IV and expected returns can be better understood.

Bali and Cakici (2008) also use the direct method. However, they note that the frequency of data used (e.g., daily or monthly), the weighting scheme used to generate average portfolio returns, the breakpoints used to sort stocks into portfolios, and the screening process for size, price, and liquidity effects can all have a material impact on the determination of IV. For example, they calculate IV, both based on daily returns across each month in their sample, and monthly returns in aggregate, and find there to be a negative relationship between IV and returns for the daily data, but no link whatsoever for the monthly data. However, after controlling for size, price, and liquidity effects, even the negative relationship that was observed when using the daily data mostly disappears.

Guo and Savickas (2006) utilize the indirect method, and define aggregate IV to be a value-weighted sum (across all stocks in a specific time period), based on the square of shocks to each stock's excess returns. Also, Jiang and Lee (2006) define IV to be the difference between average stock volatility and market volatility, which they calculate for each month between 1962 and 2002, and do on both an equally-weighted and a value-weighted basis. Meanwhile, Anrkim and Ding (2002) distinguish between cross-sectional volatility and 'intertemporal volatility,' which they define to be the variability of periodic returns over a long time horizon.

Campbell et al. (2001) try to decompose total volatility into idiosyncratic volatility, industry volatility, and market volatility, and note that idiosyncratic volatility is by far the largest component of total volatility. Guo and Savickas (2006) also found that market volatility is much smaller than IV, but the two measures differ in a very important way; that is, whereby IV is negatively related to future stock returns, market volatility is positively related to future stock returns. Goyal and Santa-Clara (2003) note that periods of high IV do not necessarily correspond with periods of high market volatility, but also state that IV represents a larger component of total stock volatility than does market volatility.

*Research Idea #1: Classify the different types of volatility employed throughout the literature, and determine the primary applications for each type when modeling volatility mathematically.*

*Note: All definitions of volatility types mentioned here are summarized succinctly in a Glossary at the end of this paper.*

*Practical Implication #1: Option traders need to know a stock's volatility because this is one of the six option pricing inputs. There is a direct relationship between a stock's volatility level and the value of both call and put option prices because when volatility increases, the expected payoff on both calls and puts must increase.*

## **EXPLANATIONS FOR VOLATILITY TRENDING UPWARD**

Both Brandt et al. (2010) and Campbell et al. (2001) observed a steady increase in idiosyncratic volatility (IV) from 1962 through 1997 for individual U.S. equities, even though aggregate market volatility and industry volatilities remained relatively constant during this period. The average volatility of the most volatile stocks in the 1990s was 2-3 times larger than that of the most volatile stocks in the 1960s, and the average volatility of firm-level profitability rose 4-5 times from the 1960s to the late 1990s (Zhang, 2005). However, Xu and Malkiel (2003) found that there has been no tendency for the most stable stocks to have increased (or decreased) in volatility over time. Most of this increase occurred during the 1970s and 1980s, so that the increase in volatility from the 1980s to 1990s is smaller than what is commonly thought.

While firm-specific IV increased even further through the Internet bubble of 1999-2001, it then fell dramatically by the bull market run of 2005-2007 (Menchero & Morozov, 2011). Brandt et al. (2010) also observed a substantial decline in IV to normal long-term levels by 2003, and claimed that the same drivers of increasing IV in the late 1990s were just as responsible for IV falling again. Most importantly, it appears that volatility data arrives in 'episodes' rather than via 'trends.' Zhang (2010) also observed stock volatility increasing from 1976-2000, but reversing dramatically from 2001-2006 (with a brief upward surge in 2002). By 2006, volatility levels were back to what they had been in the 1970s. However, starting in late 2007, stock return volatilities started to climb again, and reached their all-time high in October 2008 (Zhang, 2010).

The prevailing explanations for the long-term trend of increasing IV for equities have included increased institutional ownership, increased volatilities of firm fundamentals, newly listed firms getting younger and riskier, and product markets getting more competitive (Brandt et al., 2010). For example, firms are issuing stock much earlier in their life stage now, when there is often no earnings record or significant long-term prospects. Between 1976 and 2000, the number of stocks on major U.S. exchanges doubled. This may be because, around 1980, it became easier for new firms to get listed (especially on NASDAQ), as they no longer had to show a sustained history of profits to qualify. Furthermore, many of the newer stocks are smaller, growth stocks with higher volatilities for both earnings and returns. From 1976 to 2000, average

ROE levels in the U.S. declined while the variability of these ROE reports increased (Wei & Zhang, 2006).

Another possible cause for increasing volatility is that investors have had increasing access to inexpensive trading opportunities, and have been able to both 'day-trade' and partake in 'financial innovation' that was previously only done by corporate and institutional investors (Anrkim & Ding, 2010; Campbell, et al., 2001). Although 24-hour trading is now possible, stock return volatility is higher when stock exchanges are open (Schwert, 1989). Also, idiosyncratic volatility, at least from 1975 to 1998, was almost twice as large for NASDAQ stocks, as compared to NYSE or AMEX stocks; in fact, the increases in volatility observed since 1984 have been almost entirely from NASDAQ stocks, since volatility for NYSE/AMEX stocks has remained quite stable recently (Xu & Malkiel, 2003).

Also, the percentage of total equity held by institutions (as opposed to individual investors) increased 8-fold from 1950 to 1998, and by 1998, about half of total volume was from block trades consisting of more than 10,000 shares from institutions (Xu & Malkiel, 2003). Campbell et al. (2001) suggest two additional theories: more variability in cash flow shocks (compared to what is previously expected), and more variability in discount rate changes. They claim that as conglomerates are increasingly broken up into smaller, more distinct, and less diversified parts, there arises higher variability in cash flow streams over time. Also, as executives are increasingly given huge incentives to take more risks in order to maximize their expected compensation, this also favors less stability in cash flow streams. Brandt et al. (2010) found that IV also increases as the ratio of a stock's market value to book value increases, and that firms with low stock prices are the primary drivers of the increasing trend in IV through the late 1990s and early 2000s.

Campbell et al. (2001) also observed that volatility levels vary substantially across industry, and even more so than the IV levels for specific firms within the same industry. The computer, telecommunications, and retail sectors have had the largest recent upward trends in volatility. Xu and Malkiel (2003) acknowledge that the increased prominence of stocks listed on NASDAQ is related to the upward trend in IV, but also attribute this rise to the corporate objectives of many firms to pursue higher growth. They also posit that the volatility of individual stocks has increased recently even though overall market volatility has remained stable, a paradox which can be explained by declining correlations among stock returns. From a portfolio management perspective, this trend implies that the importance of diversification is increasing.

*Research Idea #2: As volatility has been trending upward, the importance of diversifying one's portfolio has increased. Compare the benefits of diversification in both high-volatility and low-volatility environments using a simulation approach.*

*Practical Implication #2: It is important to be able to identify whether the present 'volatility environment' is low or high, relative to long-term historical levels because there are established links between both present volatility and future volatility, and between present volatility and future expected returns; thus, current volatility levels impacts investment decisions.*

## **DETERMINANTS OF CROSS-SECTIONAL VOLATILITY**

The tracking of cross-sectional volatility helps identify variability in returns among the best and worst performing portfolio managers. Cross-sectional volatility will either rise with an increase in sector volatility, keeping the correlations of returns among sectors held constant, or with a decrease in cross-sector correlations, keeping sector volatility constant. In 1999-2000, sector

volatility rose and cross-sector correlation declined simultaneously, creating a sudden and dramatic rise in cross-sectional volatility coincident with the technology boom and bust (Ankrim & Ding, 2002).

When seeking to identify the determinants of volatility levels, both macroeconomic and microeconomic effects should be considered. First, from a macro-level perspective, volatility is heavily influenced by the variability of interest rates, and the magnitude of change within the current business cycle. If firms have large fixed costs (i.e. – operating leverage), profits will fall during recessions as demand falls; in fact, volatility is higher during recessions, since stock prices fall both before and during these times. Behavioral patterns (e.g. – a ‘follow the herd’ mentality’) may magnify such effects, since stock prices tend to change more dramatically than the fundamentals would imply (e.g. - changes in the expectations of future dividends). In other words, investors often will overreact to new information (Fridson, 2011). Other macroeconomic factors include the extent of financial leverage assumed in the market, the extent of volatility in bond prices, whether or not a fad or bubble is under way, the variability of inflation rates, the rate of money growth, and trends in industrial production (Schwert, 1989).

When firms increase the proportion of debt in their capital allocation, thereby assuming more financial leverage, stock volatility will increase. Xu and Malkiel (2003) observed that firms with high growth strategies need to reinvent themselves from time to time, which requires investing in many high-risk projects, thus leading to higher firm-specific volatility. This relationship between growth rates and volatility can be non-linear; for growth rates above 5%, the relationship is positive and approximately linear, but for low or negative growth rates, there is an inverse relationship, since such firms are more likely to be in financial distress. Brandt et al. (2010) also find that volatility is higher for stocks that have performed poorly in the past, have lower liquidity, and do not pay any dividends.

NASDAQ stocks are relatively more volatile because they tend to include smaller companies, which have lower average stock prices than NYSE/AMEX stocks, and volatility has shown to be inversely related to both size and price. Jiang and Lee (2006) state that smaller firms tend to have higher returns, but with also larger volatilities than smaller firms. Xu and Malkiel (2003) also find that volatility is inversely related to firm size. Campbell et al. (2001) find that both levels and trends for volatility are stronger for smaller firms, and also that volatility is inversely related to future output growth. Brandt et al. (2010) focus more on stock prices than firm size, and state that volatility levels for low-priced stocks are 2-3 times higher than that for high-priced stocks. Even after stock splits, they observe an increase in idiosyncratic volatility. They also find that volatility is higher among NASDAQ stocks (which have more low-priced stocks), relative to NYSE/AMEX stocks. While Xu and Malkiel (2003) establish a positive link between volatility levels and the percentage of institutional ownership in equities, Brandt et al. (2010) establish the opposite link, since retail investors typically prefer lower-priced, smaller-sized stocks that often exhibit higher volatility.

Other studies have linked idiosyncratic volatility to various firm fundamentals, like earnings per share (EPS), return on equity (ROE), or cash flows. For example, Fridson (2011) states that stocks with more variability in EPS reports over time have higher volatility, finding that this single factor accounts for at least 45% of volatility differences among the 30 Dow Jones stocks. Most researchers have chosen to focus on earnings rather than dividends, since dividend levels are under the discretion of corporate managers, whereas earnings are a better reflection of a firm’s true performance and future prospects. Smaller firms have even more variability in ROE levels than larger firms. As earnings, cash flows, and ROE levels fall, this signals trouble ahead, which causes investor jitters; however, if these shocks are positive, this tends to both lower upcoming

uncertainty and increase stock prices (Wei & Zhang, 2006). Zhang (2010) agrees that the variability in ROE levels is useful in explaining return volatilities, especially for smaller and younger firms.

*Research Idea #3: Volatility levels have been linked to macroeconomic factors like the variability of interest rates and the current state of the business cycle. Verify whether or not these links still apply in recent years, when we have seen unusually low interest rates and some rather dramatic extremes in the past business cycle.*

*Practical Implication #3: Although firms cannot do much to control the macroeconomic factors that impact volatility, they can potentially affect the idiosyncratic volatility of their own stock. For example, a firm's capital structure can impact volatility, since the more financial leverage a firm takes on, the more risky their asset cash flows are. Also, firms that decide to pursue high-growth strategies are willing to assume higher volatility in the hope of achieving higher returns.*

## **THE RELATIONSHIP BETWEEN RETURN AND VOLATILITY**

Stocks with large, positive sensitivities to market volatility tend to have lower average returns, and periods of high volatility tend to coincide with downward market movements. Furthermore, Ang et al. (2006) found that stocks with high 'idiosyncratic volatility' (IV) also have lower average returns; in fact, between 1986 and 2000, stocks in the highest-volatility quintile underperformed stocks in the lowest-volatility quintile by about 1% per month. Also, Blitz and Van Vliet (2007) observed that, for both U.S. and non-U.S. markets, stocks with the lowest historical volatility have a statistically significant positive alpha, whereas those with the greatest volatility are especially unattractive. However, they also noted that this relationship disappears if the investment universe is restricted to large-cap stocks. Darnell (2009) used U.S. equity data from 2004-2008, and found that the correlation between returns on the S&P 500 and changes in the VIX was -0.8, meaning that there was a strong, inverse relationship between volatility levels and the performance of the S&P 500 index. Meanwhile, Wei and Zhang (2006) found that ROEs and the Variance of ROEs are also negatively correlated, and that most of the recent upward trend in volatility can be explained by both the downward trend in ROE levels and the upward trend in the variance of these levels.

One explanation for the possibly negative link between volatility and return is the asymmetry of returns across business cycles; that is, stocks with high volatility may have normal average returns in 'up' markets but have lower than average returns in 'down' markets, thus creating lower than average returns overall. This may be because risk-averse agents will reduce the positions of their investments in the presence of increased uncertainty about future returns (Ang, et al., 2006). An alternative explanation is that, in up markets, increases in productivity are accompanied by increases in investment. This leads to higher growth rates, but these higher rates cannot be sustained in subsequent periods of low productivity, which then creates increasing stock volatility (Gomes, et al., 2003). Others find that high-risk stocks have lower than average returns in down markets, but higher than average returns in up markets; however, the effect from the down market dominates the effect from the up market, so that the inverse relationship between risk (i.e., volatility) and return still occurs (Blitz & Van Vliet, 2007).

The link between volatility and return is strong enough to suggest that traditional models like CAPM or the 3-factor model of Fama and French will lead to mispricing because of overreliance on a particular stock's beta (Ang, et al., 2006). For example, Blitz and Van Vliet (2007), acknowledging that volatility and beta are related measures, find that beta and a stock's return are inversely related, whereas CAPM finds them to be directly related. As a result, Bouche

(2010) suggests an adjusted CAPM relies on a quadratic rather than a linear model, where returns initially rise with increased risk, but eventually get dragged down when volatility becomes excessive. Stivers and Sun (2010) find that, in recessionary times, return dispersion is higher, and contains information that is positively linked to both subsequent market volatility, and increased unemployment. Gomes et al. (2003) also discover that the dispersion of betas is lower around business cycle peaks and higher around business cycle troughs. Also, with respect to investor sentiment, when sentiment is high, many investors will pick speculative stocks, which despite their higher risk levels, have lower future average returns than bond-like stocks (Baker & Wurgler, 2007).

In contrast, Jiang and Lee (2006) find that, after correcting for serial correlation, volatility becomes directly related to stock returns, even though this effect appears to be delayed. Many studies of stock volatility use an auto-regressive framework that includes only 1 or 2 lagged volatility measures in the regression, and by definition, do not account for volatilities being serially correlated over longer periods of time. Much more so than returns, volatilities have substantial serial correlation since future volatility levels do relate strongly to past volatility levels. Goyal and Santa Clara (2003) also find a positive relationship between 'average stock variance' and market returns, but find no link between market volatility and market returns. Here, average stock risk (in each month) is defined as the cross-sectional average of the variances of all stocks traded in a month. Since this measure is mostly driven by IV, their findings are at odds with models that state that only systematic risk should affect returns. One possible explanation for this effect: investors hold non-traded assets (e.g., human capital and private businesses), and when the risk of these assets increase, they are less willing to hold traded assets, and thus require an increase in the expected return of traded assets.

Diavatopolous, Doran, and Peterson (2008) incorporate 'implied volatility,' as measured by option prices, to explore the relationship between idiosyncratic volatility and future expected return. 'Implied volatility' is the level of volatility, based on a theoretical option pricing model (Black & Scholes, 1973), that would produce the observed market price for a particular option. Diavatopolous et al. find that market expectations, as represented by implied volatility, provide better assessments of future volatility than past volatility, as given by historical volatility. More specifically, they find a strong positive link between implied idiosyncratic volatility and future returns, but find no such link between historical volatility and future returns.

Bali and Hovakimian (2009) also incorporate implied volatility, and consider both the relationship between the realized-implied volatility spread and expected returns, and the relationship between the call-put implied volatility spread and expected returns. Implied volatilities typically exceed future realized volatilities, which creates a negative, realized-implied volatility spread (RIVS). Bali and Hovakimian find that a trading strategy that longs stocks with low (i.e., more negative) RIVS and shorts stocks with high RIVS (i.e., less negative) produces positive returns because stocks with low realized volatilities tend to have higher returns. Also, a high call-put implied volatility spread (CPIVS) indicates that call prices will exceed levels implied by put prices and put-call parity. Bali and Hovakimian also find that a trading strategy that longs stocks with high (i.e., more positive) CPIVS and shorts stocks with low CPIVS produces positive returns because stocks with high CPIVS are likely to have higher returns.

*Research Idea #4: Some believe that high-volatility stocks behave normally in 'up' markets but perform relatively poorly in 'down' markets; others believe that high-volatility stocks perform relatively well in 'up' markets and perform relatively poorly in 'down' markets, but that the 'down' market effect dominates the 'up' market effect. Explore which of these two theories is more correct.*

*Practical Implication #4: If a stock analyst can accurately estimate a firm's idiosyncratic volatility, and knows whether this level is increasing or decreasing, there may be trading opportunities that can exploit the negative link between IV and future expected returns. This is especially true for firms with either small market capitalization or a low stock price (or both).*

The next 3 sections (Factor Models..., The Momentum Anomaly, and Investor Sentiment) are primarily about stock returns rather than volatility directly. However, these sections relate materially to volatility as discussed earlier. In the upcoming section, several studies are cited which incorporate volatility as a factor. In the 'Momentum Anomaly' section, a link between momentum and idiosyncratic volatility levels is formed. Finally, in the 'Investor Sentiment' section, a link between investor sentiment and the prevailing volatility environment is established.

## **FACTOR MODELS FOR EXPLAINING EXCESS RETURN**

Fama and French (1993) identified three risk factors that were associated with returns on U.S. stocks and bonds, when using data from 1963 to 1991. In addition to the excess return of the market portfolio over the risk-free rate, which is the single factor represented in CAPM, they also found two new factors that were not previously part of CAPM. First, they identified a 'size' effect, where firms with small capitalization outperformed firms with large capitalization. Second, they identified a 'value' effect, where firms with high book-to-market value ratios (i.e. – value stocks) outperformed firms with low book-to-market value ratios (i.e. – growth stocks).

Gomes et al. (2003) also found evidence for both of these effects. However, after controlling for beta, they found that these effects vanish because both the size and book-to-market ratio of a company are correlated with a firm's beta. Also, Ang et al. (2006) incorporated volatility to develop a two-factor model to predict expected return, with the two factors being the market's excess return (as in CAPM) and daily changes in the VIX. Jeegadesh and Titman (2001) expanded the Fama and French 3-factor model to include a momentum effect, and found that this effect persisted into the 1990s, unlike the value and size effects which were only statistically significant in the original 1963-1991 period. They also found that loser stocks are more risky than winning stocks because they are more sensitive to all 3 factors from the Fama and French model. Finally, Menchero and Morazov (2011) ambitiously attempted to use a global factor model to predict returns, where their model consisted of 48 country factors, 24 industry factors, and 8 style factors. The 8 observed styles were: size, value, momentum, volatility, growth, leverage, liquidity, and non-linear size.

In the early months of 2000, when the Dow stalled but the NASDAQ continued its bull run, growth stocks outperformed value stocks by a large amount. However, after this episode, this trend reversed, and over a complete business cycle, value stocks typically outperform growth stocks. Value stocks are thought to have lower relative risk than growth stocks, so that their outperformance is evidence that is inconsistent with CAPM. Zhang (2005) found that the differential return of value stocks over growth stocks is highest in bad times, when book-to-market value ratios are at their highest.

*Research Idea #5: There have been many factor models that have predicted a stock's excess return, or separately, a stock's idiosyncratic volatility. Combine these two types of models into a unified framework, and identify a subset of factors that is associated with each measure.*

*Practical Implication #5: Traders should resist simplistic strategies that attempt to exploit the 'size' and 'value' effects from the FF3 model because these effects have not persisted since the*

*Fama and French paper identified them in 1993. However, the 'momentum' effect, as discussed in the next section, has been more persistent, especially on a short-term basis.*

## **THE MOMENTUM ANOMALY**

The 'momentum' anomaly suggests that buying stocks with recent high returns and selling stocks with recent low returns will produce superior profits over time (Arena, et al., 2008). The main proponents of this effect are Jeegadesh and Titman (1993), who found that winners from the past 3-12 months outperform losers over the next 3-12 months because markets may underreact to new information about a firm's prospects, especially in the short-term. Jeegadesh and Titman (2001) published a subsequent paper that used data from the 1990s, since their original paper only used data from 1965-1989, and unlike many other anomalies that were discovered during that period (e.g. – the 'value' and 'size' effects), the momentum effect continued to persist subsequently. In the 1990s, the returns of past winners were, on average, higher than the returns of past losers by about 1% per year. The authors offered three behavioral explanations for the success of momentum strategies. First, traders may suffer from a self-attribution bias, as they attribute the performance of past winners to stock selection skills and the performance of past losers to bad luck. Second, they may also be overconfident in their own abilities, which helps temporarily push up prices of past winners above their fundamental values. Third, traders who favor technical analysis over fundamental analysis will more often buy past winners and sell past losers.

However, after awhile, traders who favor more fundamental valuation will correct for the overreactions of the technical traders, which contributes to the reversal of price trends. Thus, while investors may underreact to new information about companies in the short-term, they also overreact to such information in the long-term, which implies that any large momentum effect is often soon thereafter accompanied by a large reversal (Arena, et al., 2008; Bhojraj & Swaminathan, 2006). Jeegadesh and Titman (1993) acknowledge that the benefits of a momentum strategy dissipate after about 12 months, and there may even be negative differential returns from such a strategy 12-30 months after portfolio formation. They also found that, with respect to earnings announcements, past winners do better 7 months later, but past losers do better 13 months later.

Stocks with higher idiosyncratic volatility (IV) often have greater momentum returns than those with lower IV, but also have quicker and larger reversals than lower IV stocks. This phenomenon occurred in the late 1990s and early 2000s, when both momentum effects and IV were abnormally strong (Arena, et al., 2008). Bulkley and Nawosah (2009) found that the momentum effect vanishes when controlling for cross-sectional variation in expected returns (which means that cross-sectional volatility is quite important in explaining momentum). Stivers and Sun (2010) used data from 1962-2005 to show that the cross-sectional return dispersion of U.S. stocks is directly related to the future excess return of 'value' strategies over 'momentum' strategies, and inversely related to this past excess return. Thus, when volatility is high, as tends to occur when bad times are ahead, value strategies perform better, but when volatility is low, as tends to occur in bull markets, momentum strategies do better.

Other factors may also affect the potential success of momentum strategies. For example, the amount of news released about a particular company contributes directly to that stock's momentum, especially if the news is unfavorable (Arena, et al., 2008). Bhojraj and Swaminathan (2006) found that this trend was most noticeable for low-to-mid-cap stocks, low-priced stocks, and less followed stocks. Jeegadesh and Titman (1993) discovered that the momentum effect is more dominant for smaller firms, and for firms with higher betas.

Furthermore, they observed some seasonality in that abnormal returns from momentum strategies are significantly greater during the months of April, November, and December, but are significantly smaller in January. They also found the momentum reversal effects to be stronger for smaller firms, and attributed this to the higher volatility of smaller-sized firms (Jeegadesh & Titman, 2001).

Leveraged ETFs (exchange-traded funds) add exposure after good performance, and remove exposure after bad performance, thus contributing to volatility risk (Bouchey, 2010). Contrarians take an opposite approach, whereby they sell assets that have recently gone up, and use the proceeds to buy other assets that have recently gone down. This strategy of 'systematic rebalancing' may work to control volatility or minimize downside risk, but requires discipline since it is contrary to human nature. Bulkley and Nawosah (2009) find that strategies that ignore momentum are consistently better than those based on recent performance, and thus claim that full sample means (over a much longer past period of time) are a better estimate of upcoming expected returns than returns observed during a much smaller past sub-period.

*Research Idea #6: Contrarians use 'systematic rebalancing' to sell assets in 'up' markets and buy assets in 'down' markets, thus managing volatility, whereas leveraged ETFs take the opposite approach, thus assuming more volatility risk. Compare the returns of these strategies in both high-volatility environments and low-volatility environments using a simulation approach.*

*Practical Implication #6: Technical analysts often exploit the 'momentum' effect to their advantage. To review, winning stocks from the past 3-12 months outperform losing stocks over the next 3-12 months; however, after this future period expires, these same stocks may have inferior returns over subsequent time periods due to a reestablishment of investors beliefs.*

## **INVESTOR SENTIMENT**

Evidence from the behavioral finance literature has indicated that investors are subject to sentiment, and that there are times when betting against this sentiment can be both costly and risky (Baker & Wurgler, 2007). For example, in the late 1990s, investor sentiment for speculative and difficult-to-value technology stocks helped push prices to ultra-high levels, which was shortly followed by a severe market correction. During times of high sentiment, stock price changes will be much larger in magnitude than what would be justifiable based on dividend-based valuation models (Shiller, 1981). Portfolio managers often have incentives to invest in speculative stocks, as they may be compensated based on the ability to obtain a higher alpha. This incentive structure can lead to the overpricing of high-risk stocks (and underpricing of low-risk stocks) since new money tends to flow toward assets that have done well in the recent past. Investment managers are more willing to overpay for risky, high-volatility stocks, especially in a 'layered' investment approach, where there is a lower-risk, safer layer that is designed to avoid poverty and a higher-risk, more speculative layer that is designed to procure some huge positive returns (Blitz and Van Vliet, 2007).

Investor sentiment is difficult to measure directly, but proxies like trading volume and liquidity measures can be used to indirectly infer what the market's prevailing mood might be. A stock's bid-ask spread is inversely related to its liquidity. Guo and Savickas (2006) found that bid-ask spread is directly related to future excess stock returns, but that volume or turnover is inversely related to future excess stock returns. A stock's idiosyncratic volatility (IV) is also used as a proxy for both its liquidity risk and dispersion of opinion. When IV rises in an 'up market', this may be indicative of investor overconfidence which can lead to substantial investment mistakes (Brandt, et al., 2010).

The stocks of smaller and younger companies with a shorter record of profitability are typically subject to higher levels of investor sentiment. These stocks have above-average volatility, pay fewer dividends (if any at all), and are often growth companies. Furthermore, they have little to no earnings history, and are often valued based on prevailing sentiment rather than on firm fundamentals. Thus, such stocks do relatively well when the market is booming, since this is exactly when the propensity to speculate is the highest. Stocks of firms in financial distress (whether young or more established) are also subject to broad waves of investor sentiment, and are difficult to both arbitrage and value in general (Baker & Wurgler, 2007).

*Research Idea #7: Some investment managers knowingly speculate on risky, high-volatility stocks, hoping that at least a small number of these investments will achieve ultra-high returns. Perform a retrospective study of the most volatile stocks, and after adjusting for risk, observe the proportion that had very high returns, the proportion that had very low returns, and the amount of value gained by the winning stocks relative to the amount of value lost by the losing stocks.*

*Practical Implication #7: In the early stages for when investor sentiment is high, it is risky to be on the sidelines while a market overreaction is contributing to rising prices; however, after investor sentiment has been high for some time, the risk becomes that of a market correction, whereby stock prices fall back to their fundamental-based 'intrinsic value;' Be cautious when investor sentiment (on a particular stock) is high, but the stock's idiosyncratic volatility is rising.*

In the remaining sections, the focus switches from a discussion on idiosyncratic volatility trends to an overview of recent 'extreme volatility' events. Note that these are two separate constructs, whereby the main difference is that 'extreme volatility' events are much less predictable than IV patterns, and often occur without any prior warning. Although the number of 'extreme volatility' events is positively correlated with the prevailing volatility environment, these events can and do also occur during low-volatility regimes. It is challenging to hedge against the risk of such events, but both liquidity management and derivatives can be utilized, each of which is discussed below.

## **EXAMPLES OF EXTREME VOLATILITY EVENTS**

In addition to identifying trends in volatility over long periods of time, one can also focus on shorter-term events that lead to extreme market volatility. Although the definition of 'extreme' is somewhat arbitrary, Brandt et al. (2010) define 'attention grabbing events' as "days where a stock's return is at least 3 standard deviations higher or at least 1.5 standard deviations lower than the mean daily return on that stock, or where the daily turnover is at least 3 standard deviations higher than the mean turnover level." Although overall market volatility has not increased substantially through time, firm-specific IV has increased, and on any particular trading day, the most volatile stocks typically move by very large percentages, often 25% or more (Campbell, et al., 2001). Xu and Malkiel (2003) isolate individual stocks that endured price changes of at least 25% in a single day, and find that this most often occurs when reported earnings are different from earlier forecasts, especially if such earnings updates fall short of prior expectations. The majority of institutional investors will react swiftly, and in similar fashion, to announcements of earnings surprises. Waller (2009) analyzes extreme market volatility by counting the number of occurrences in a calendar year where the closing value of the Dow Jones Industrial Average is at least 1% changed from the previous daily close. In 2008, 134 of the 253 trading days, or 53% of all days observed had at least a 1% change in the DJIA, which was a level of 'volatility' not observed in the markets since the early 1930s. This proportion was

more than 3 times larger than the average ratio of 15.6% observed in the relatively quiet days of the period from 2004 to 2007.

Times of extreme volatility also tend to be times of extreme illiquidity in the market. For example, there was a large volatility spike in October 1987, when the VIX (calculated retrospectively after its inception in 1993) jumped from 22% at the start of the month to 61% by month's end; this was due to the portfolio insurance meltdown on October 19, 1987. Also, in late August 1998, the VIX suddenly reached 48% due to fears that the Russian government would either devalue the ruble or default on government bonds (or both). In contrast, the average level of the VIX between 1986 and 2000 was only approximately 22% (Ang, et al., 2006). On August 13, 1998, Russian markets were closed for 35 minutes due to severe illiquidity and downward price pressure. In the recent financial crisis, the Dow fell 49% between October 2007 and February 2009 amid very high (and persistently high) volatility levels, levels that were even higher than that observed between 1998 and 2002. Volatility levels were higher in 1987 than observed during the financial crisis, but this was almost entirely due to one day (October 19, 1987). Guo and Savickas (2006), when attempting to study volatility over long periods of time, replaced observed volatility levels on October 19, 1987 with the 2nd largest observation in the sample sub-period, so as to not confound the rest of their analysis. The only calendar year in U.S. financial history that had volatility patterns similar to that observed in 2008 (and the first quarter of 2009) was 1937 (Darnell, 2009). Finally, the 'flash crash' of May 6, 2010, which related to high-volume, technologically-advanced trading, also occurred amid unusually high volatility and thinning liquidity.

A hot research topic in actuarial science the past 10-15 years has been the modeling of tail risk. This was especially prevalent during the recent financial crisis since prior models failed to adequately estimate either the frequency or severity of 'tail-type' events in 2007 or 2008 (Darnell, 2009). Many of these prior models, such as those based on the Markowitz framework from the early 1960s, had relied on the assumption that price changes follow a normal distribution. However, empirical data has repeatedly shown that extreme price changes (which are captured in the tails) occur more frequently than what a 'normal' distribution, or a Geometric Brownian motion framework, would predict (Farmer, et al., 2004). Now, the consensus is that a non-Gaussian, fatter-tailed distribution should be employed to model stock returns, and if possible, the volatility of these returns should be allowed to fluctuate through time. Fuentes et al. (2009) believe that, on any given trading day, returns are actually well described by a normal distribution, but across longer timeframes, this characterization will change due to volatility levels drifting over time.

Darnell (2009) identifies the primary drivers of tail events as currency crises, defaults by sovereign bond issuers, terrorist events, or anything else that investors would have a difficult time imagining in advance. Many practitioners believe that such events cannot be captured by a quantitative model, but rather, investors should simply use good judgment (based on past experience) to anticipate these events. Tails on the low end of the return distribution are now fatter (and more frequently observed) than they were 15-20 years ago because of the greater systemic risk that permeates the markets. However, stocks that are more heavily traded, and thus have ample liquidity, are largely immune to this increasing prevalence of extreme volatility (Farmer, et al., 2004). Shiller (1981) observed that stock price change distributions not only had fat tails, but high kurtosis (i.e., – low peakedness around a mean level), and attributed this effect to the tendency for new information about stocks to arrive in big jumps (and at unpredictable times), rather than arriving in a more smooth, continuous fashion.

*Research Idea #8: There has been much recent attention in financial and actuarial research on quantifying tail risk, with focus on managing downside risk. Compare the behavior of the upper tails to that of the lower tails, and determine which tail occurs more often, or in greater deviation from the mean, than the other tail.*

*Practical Implication #8: In the past 25 years, tail risk events have occurred with higher frequency (and with greater severity) than traditional financial models would have predicted. This is partly because contagion effects are stronger now than they had been before. On the plus side, these 'extreme volatility' events have partly led to the creation and development of 'enterprise risk management' in many corporations.*

## **MANAGING LIQUIDITY AMID EXTREME VOLATILITY**

Liquidity problems occur when changes in supply and demand do not occur in orderly fashion, which causes volatility changes to be more pronounced. For example, if there are gaps in filled price levels in the limit order book, illiquidity will result (Farmer, et al., 2004). When a significant news event occurs, either in relation to a specific company or the market as a whole, trading volume will be higher when there is a wider dispersion of investor beliefs. This dispersion will temporarily lead to higher volatility, that is, until the market has fully processed the new information and equilibrium is reestablished (Lee, et al., 1994). Schwert (1989) asserts three reasons for a positive relationship between volume and volatility. First, new information causes changes in both prices and trading patterns by necessity, especially if there are differences in how to interpret the information. Second, some investors base trading decisions purely on price movements, so that large price changes will naturally beget larger trading volume. Third, if there is short-term price pressure due to illiquidity, large trading volume in one direction (either buy or sell) will cause price movements (either up or down, respectively). The main categories for news events that primarily affect a single company include: acquisitions and divestitures, capital structure changes, takeovers and leveraged buyouts, legal news, and general financial information. The most frequently observed category is takeover announcements (Lee, et al., 1994).

To illustrate liquidity management during crises that are broad enough to affect the entire market, we can focus on extreme volatility events, such as the October 1987 and October 1997 crashes. After the 1987 crash, some regulators suggested that circuit breakers be introduced so that the market could buy time to process any new information that may adversely affect prices during times of insufficient liquidity balance. This would (theoretically) lower the information asymmetries between traders, and would permit the orderly emergence of new consensus prices (Lee, et al., 1994). Soon thereafter, circuit breakers were actually put in place, but they did not prove to be effective in managing future extreme volatility events. On October 27, 1997, investors who were afraid that circuit breakers would kick in and close the market prematurely, started a large selloff that accelerated price declines in the last minutes of trading before the circuit breakers were actually implemented. After an initial 350 point decline, there was a 30-minute trading halt, and after the market reopened, the Dow lost an additional 200 points, which then triggered a 2nd early market shutdown. In all, the DJIA lost 7% of its total value that day. Soon afterwards, the NYSE decided to ease the levels at which circuit breakers were activated, and on September 1, 1998, these looser standards allowed the markets to remain open until normal closing time, even though the Dow plummeted by over 500 points that day. The new standards required a one-hour trading halt, but only if the market dropped by 20% before 2:00p EST, a 30-minute break if the drop occurred before 2:30p, and no break being allowed after that time. In the end, circuit breakers were deemed ineffective

because they simply transferred selling pressure from the stock market to the growing futures market (Keegan, 1998).

Lee et al. (1994) studied the effects of firm-specific trading halts on the NYSE, which were characterized as occurring during “unusual market situations,” lasting about an hour, and consisting of an average absolute change in return of about 8%. They also found trading halts to be ineffective, claiming that they neither reduced trading volume or price volatility; that is, the halts did not achieve the goal of creating a ‘calming down’ period that would allow for the emergence of a new consensus price in an orderly fashion. To the contrary, volume and volatility were even higher in the 1-3 day period after a trading halt than that observed before the halt. This may be because various traders (during a halt) are unwilling or unable to reveal their true demands fully. Furthermore, Lee et.al. (1994) acknowledge that, in times of around-the-clock financial media coverage, the press may exasperate these negative effects as investors dump their holdings in fear that they may otherwise suffer even greater losses. Approximately 75% of all trading halts simply resulted in delayed market openings, rather than actually stopping trading in the middle of a trading period. There is also evidence of a momentum effect upon trading halts, whereby once markets reopen after halts caused by upward price pressure, day-1 returns are positive, but once they reopen after halts caused by downward price pressure, day-1 returns are negative. Most of the wildest price swings take place within the first half-hour, though, after markets reopen. Surprisingly, the majority of trading halts are imposed upon the receipt of news that contributed to increases in a particular stock price, usually when a firm is announced as a takeover target.

*Research Idea #9: Determine the leading reasons for past examples of extreme volatility in U.S. equity markets, as identified by daily % changes in major market indices above a specified threshold, and comment on whether this ranking has changed through time.*

*Note: An overview of the top 100 most volatile days in the S&P 500 index between 2000-2012, with proposed reasons for these events, is provided in the ‘Appendix.’*

*Practical Implication #9: A liquidity crisis in the stock market results primarily from an imbalance between buyers and sellers. This typically occurs in special circumstances, such as right after a major news announcement that either affects an individual stock or the market as a whole. Circuit breakers and trading halts have been used to manage extreme illiquidity, but these tools have been largely unsuccessful.*

## **MANAGING VOLATILITY WITH DERIVATIVES**

The two major uses for derivatives are speculation and hedging. When speculating with derivatives, a particular market view is adapted, and if correct, due to the potential benefits of financial leverage, the return will be magnified relative to investing only in the underlying asset. With hedging, one attempts to reduce portfolio risk by using derivatives that have payoffs that vary inversely with that of the underlying asset, thus limiting potential losses. Volatility can be managed directly using some combination of call and put options in both hedging and speculating contexts. For example, from a hedging perspective, one can lock in a desired volatility level by using the right allotment of long puts and short calls. Moreover, the premiums from the short calls can be used to offset the premiums from the long puts so that the desired volatility exposure can be obtained at no cost (Bouchey, 2010).

Options can also be used to speculate on future volatility levels, whereby one either takes long or short positions as to the direction that volatility will move. Long volatility positions, obtained

by buying either call or put options, are like insurance in that they lose money most often, but also provide downside protection; that is, the option premiums must be paid up front whether the options eventually have positive payoffs or not. The expected payoffs will increase as volatility increases, hence the position being labeled 'long volatility.' Traders that believe volatility will rise in the future can either buy options, straddles or strangles to capitalize on this view if correct. A straddle consists of a long call and a long put on the same stock such that both options have the same strike price and time to expiration. A strangle is similar to a straddle except that now, both options are out-of-the-money, so as to reduce the overall premium outlay. Such buyers should beware, though, if the volatility environment is already high at the time such options are purchased, since periods of prolonged high volatility are often followed by periods of prolonged low volatility (Waller, 2009).

In contrast, short volatility positions, obtained by selling either call or put options (or writing straddles or strangles), are like selling insurance. Although the expected profit on such strategies is positive, there is also heavy, potentially unlimited, exposure to downside tail risk if volatility increases in the future. In the mid-2000s, a strong preference existed for 'short volatility positions,' since the premiums received from these positions exceeded the payoffs that were ultimately made. However, once the financial crisis occurred, this relationship dramatically reversed. If investors want superior returns in down markets, it is more appropriate to use a mix of Treasuries, short sales, and derivatives consistent with 'long volatility positions' (Darnell, 2009).

*Research Idea #10: Conduct a historical comparison between 'long volatility' and 'short volatility' positions/strategies, using either real option pricing data or simulation techniques, and demonstrate why speculating on future volatility levels is so risky.*

*Practical Implication #10: Derivatives are the primary tool that investment professionals utilize to manage volatility, whether reducing risk by hedging or leveraging risk by speculating on the future volatility trend. Examples of such tools include call options, put options, straddles and strangles. Note that an episode of high volatility is often followed by an episode of low volatility, and vice-versa.*

## **CONCLUSION: SUMMARY OF KEY FINDINGS**

The three primary purposes of this paper have been to:

- Establish the importance of understanding volatility amid the new 'high volatility' environment so that investors are more informed to make decisions about risk and return in a unified framework.
- Review the recent literature on volatility research, with particular focus on idiosyncratic volatility, the reasons for why it has increased, the factors that affect its level, and the relationship between IV levels and future expected return.
- Suggest ten ideas for future volatility research (as relates to the prior literature review), while identifying ten associated practical implications that may be of interest to both academics and practitioners.

The most essential findings from this paper, as linked to the primary question of interest for each section, are organized as shown in Table 1.

**TABLE1. SUMMARY OF MOST ESSENTIAL FINDINGS (by Section)**

No.	Section Title	Most Essential Findings
1	Idiosyncratic Volatility (IV)	<ul style="list-style-type: none"> <li>• IV isolates the price risk for an individual firm</li> <li>• There are 2 approaches for estimating IV: taking the variance of residuals from a factor model for excess returns (direct method), and taking the difference between the total variance of stock returns and the variance of market returns</li> </ul>
2	Explanations for Volatility Trending Upward	<ul style="list-style-type: none"> <li>• Increased institutional ownership</li> <li>• Increased volatilities of firm fundamentals</li> <li>• Newly listed firms are becoming younger and riskier</li> <li>• Product markets are becoming more competitive</li> <li>• Corporate objectives to pursue higher growth</li> </ul>
3	Determinants of Cross-Sectional Volatility	<ul style="list-style-type: none"> <li>• Macroeconomic Effects: variability of interest rates, characterization of the business cycle</li> <li>• Microeconomic effects: extent to which firms employ financial leverage, recent stock returns</li> </ul>
4	The Relationship Between Return and Volatility	<ul style="list-style-type: none"> <li>• Market volatility is negatively associated with market returns, especially in recessionary times</li> <li>• For idiosyncratic volatility, the corresponding evidence is inconclusive; many also found a negative link, but others, after controlling for firm size, found no such link</li> </ul>
5	Factor Models for Explaining Excess Return	<ul style="list-style-type: none"> <li>• CAPM uses 'market risk premium' only</li> <li>• FF3 also incorporates 'size' and 'value' effects</li> <li>• Others also incorporate a 'momentum' effect</li> <li>• Loser stocks are especially sensitive to these factors</li> </ul>
6	The Momentum Anomaly	<ul style="list-style-type: none"> <li>• Initially, buying winner stocks and selling loser stocks is a winning strategy (for 3-12 months)</li> <li>• However, thereafter, there is a momentum reversal, whereby past winners underperform</li> <li>• Stocks with higher IV have more momentum</li> </ul>
7	Investor Sentiment	<ul style="list-style-type: none"> <li>• During times of high sentiment, the market will overreact, relative to what the fundamentals say</li> <li>• When IV rises in 'up' markets, this reflects investor overconfidence and a poor attempt to increase alpha</li> </ul>
8	Examples of Extreme Volatility Events	<ul style="list-style-type: none"> <li>• An 'extreme volatility' event can be defined in terms of abnormal price changes or volume levels</li> <li>• Examples include Portfolio Insurance (10/19/87), the Russian crisis (8/13/98), the recent Financial Crisis (late 2007 – early 2009), and the Flash Crash (5/6/10)</li> </ul>
9	Managing Liquidity Amid Extreme Volatility	<ul style="list-style-type: none"> <li>• Illiquidity can cause a short-term volatility spike</li> <li>• Volatility will be higher when there is a wider dispersion of investor beliefs, especially before market corrections</li> <li>• Circuit breakers and trading halts have been largely ineffective at managing volatility spikes</li> </ul>
10	Managing Volatility with Derivatives	<ul style="list-style-type: none"> <li>• Options (Calls and Puts) and Option Strategies (Straddles and Strangles) can be used to either hedge volatility risk or speculate on future volatility levels</li> <li>• Both long and short volatility positions are possible; long positions are safer but have lower expected return</li> </ul>

## **FUTURE RESEARCH RELATING TO EXTREME VOLATILITY**

There is still much research to be done in order to understand volatility trends, factors that affect volatility at both the company and market levels, and the management of volatility amid conditions of economic duress. This is especially true for extreme volatility events, since the finance literature has much less complete coverage on this topic.

For example, what happens to the markets 1 day, 2 days, 1 week, etc., after these extreme volatility events occur; that is, do these short-term volatility episodes persist, and if so, do prices continue in their current direction, or is there a market correction? Many of the most dramatic price movements are simply results of market corrections (after an earlier overreaction by investors). Thus, any methodology that could identify whether extreme movements are part of a sustained bull or bear market versus a simple market correction would be helpful. Finally, this paper has focused predominantly on U.S. markets, but one could also compare extreme market volatility in the U.S. to that of other developed (and developing) world markets. Furthermore, do volatility trends in U.S. markets tend to lead other world markets, or lag in reaction to them?

Extreme volatility can also be analyzed at levels smaller than the market itself. For example, which industries experience the most financial instability, and does the answer to this question vary within or among business cycles? One could consider all of the stocks on U.S. exchanges that have experienced extreme movements (e.g. – price changes of at least 25%) between consecutive trading days, and identify some common factors among these stocks. In addition, among all of these firm-specific occurrences, what proportion of these events can be attributed to extreme volatility in the markets on those days versus the proportion that have explanations that are more isolated to a particular firm? Also, what does the recent data reveal about the relationship between firm-specific volatility and subsequent realized returns, both during and after the financial crisis? Finally, as models from both the 'behavioral finance' and 'technical analysis' literature continue to develop, how can they be used to better understand the decisions of investors amid essential moments in price change history?

## GLOSSARY: VOLATILITY TYPES AND DEFINITIONS

VOLATILITY TYPE	DEFINITION
'Bad' volatility	Volatility due to political risk, systematic risk, and other country-specific forces that firms cannot control, which tends to prevent growth and productivity, and promote instability
Cross-sectional volatility	The dispersion of stock returns over a single sub-period of time
Expected idiosyncratic volatility	The volatility resulting from an AR(2) time series model, which uses the idiosyncratic volatility from the past two months as predictive factors
Fama-and-French idiosyncratic volatility	See Idiosyncratic volatility, except now the residuals are based on a model that contains three factors: size, value, and market return
Firm-specific volatility	See Idiosyncratic volatility
'Good' volatility	Volatility due to conditions associated with greater economic welfare, like greater incentives for firms to take risk, become more innovative, and pursue growth strategies
Historical volatility	The standard deviation of a stock's continuously compounded returns over a past period of time
Idiosyncratic volatility	An estimate of an individual firm's current volatility level, which is usually based on the standard deviation of the residuals from a factor model for excess returns
Implied volatility	The specific volatility level that, according to a theoretical option pricing model, would produce the observed option price on the market
Industry-level volatility	The volatility of a specific industry's returns across a single period of time
Intertemporal volatility	The dispersion of periodic stock returns over a long time horizon
Market volatility	The volatility of the market return across a single period of time
Total volatility	The sum of idiosyncratic volatility, industry-level volatility, and market volatility; also, see historical volatility
Unexpected idiosyncratic volatility	The difference between idiosyncratic volatility and expected idiosyncratic volatility
VIX	A volatility index, which measures the implied volatility of synthetic, one-month, at-the-money options on the S&P 500 index

## APPENDIX

### THE TOP 100 MOST VOLATILE DAYS IN S&P 500 INDEX, 2000-2012, AS MEASURED BY DAILY % PRICE CHANGE

Year	# of Days in Top 100	Dates of 'Up' Days	Dates of 'Down' Days
2000	5	3/16, 10/19, 12/5	1/4, 4/14
2001	7	1/3, 4/5, 4/18, 9/24	3/12, 4/3, 9/17
2002	14	5/8, 7/5, 7/24, 7/29, 8/14, 10/1, 10/10, 10/11, 10/15	7/10, 7/19, 7/22, 8/5, 9/3
2003	3	3/13, 3/17	3/24
2004	0	-	-
2005	0	-	-
2006	0	-	-
2007	1	-	2/27
2008	38	3/11, 3/18, 4/1, 9/18, 9/19, 9/30, 10/13, 10/16, 10/20, 10/28, 11/4, 11/13, 11/21, 11/24, 11/26, 12/2, 12/5, 12/8, 12/16	9/9, 9/15, 9/17, 9/22, 9/29, 10/2, 10/6, 10/7, 10/9, 10/15, 10/22, 10/24, 11/5, 11/6, 11/12, 11/14, 11/19, 11/20, 12/1
2009	18	1/21, 1/28, 2/24, 3/10, 3/12, 3/23, 4/9, 5/4	1/14, 1/20, 1/29, 2/10, 2/17, 2/23, 3/2, 3/5, 3/30, 4/20
2010	3	5/10	5/20, 6/4
2011	11	8/9, 8/11, 8/23, 10/10, 10/27, 11/30	8/4, 8/8, 8/10, 8/18, 11/9
2012	0	-	-

Note: To be in the top 100 (shown above), the daily % price change, as defined by the natural log of the ratio between consecutive daily closing prices, had to be at least 3.30% in either direction; 52 of 100 days were 'up' moves and 48 of 100 were 'down' moves.

The four primary categories for the main drivers of these price changes were:

- New information relating to macroeconomic data (approximately 1/3 of the occurrences)
- Market corrections in the opposite direction from what had occurred in days before (1/3)
- New information relating to company-specific announcements (1/6)
- Policy announcements (current/actual or future/expected) from the Federal Reserve (1/6)

### **Key Finance Events Relating to Particular Volatility Episodes, 2000-2012:**

- 3/12/01-4/18/01: earnings of technology firms different than prior expectations
- 9/17/01-9/24/01: market effects from the terrorist attacks of September 11, 2001
- 7/5/02-10/15/02: investors lose trust due to accounting scandals (e.g., Enron, Worldcom)
- 3/13/03-3/24/03: uncertainty about the extent of upcoming U.S. activity in Iraq
- 3/11/08-4/01/08: positively received efforts by the Fed. Reserve to address 'credit crunch'
- 9/9/08-12/16/08: peak months of banking/financial crisis (e.g., Lehman Bro., AIG, Citi)
- 1/14/09-5/4/09: government bailouts are made to banks and auto companies
- 5/10/10-6/4/10: trouble throughout world markets, especially in European banks
- 8/4/11-8/23/11: downgrade of U.S. debt and associated Fed stimulus programs
- 10/10/11-11/30/11: solutions proposed to help control European debt crisis

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