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**Check Yourself Before You Wreck Your Wealth:**  
**The Effects of the Business Cycle on Stock Market Efficiency**

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## **Abstract**

The Efficient Markets Hypothesis (EMH) has been financial dogma since the 1970s. As a cornerstone of modern financial theory, the EMH influences many financial models and investment decisions. With varying levels of estimated efficiency, the EMH can be categorized into three forms: weak, semi-strong, and strong. Two defining characteristics of the EMH are that securities prices are accurate reflections of all available information, and above-average returns cannot be maintained without above-average risks. Essentially, this hypothesis maintains that investors cannot “beat the market.” I investigate the effects that the business cycle may have on efficiency in the U.S. stock market. The purpose of this research is to analyze market efficiency during expansions and contractions of the business cycle. Using historical monthly S&P 500 data returns as a benchmark, I examine monthly returns of a sample of mutual funds and ETFs. I compare these returns with the Capital Asset Pricing Model (CAPM) to determine the degree of efficiency throughout the business cycle.

## **Introduction**

Evolution is a remarkable phenomenon. Without ancestral modification, the world, as we experience it today, could not exist. It is hard to imagine primitive mammals developing any sort of trade system, let alone the complex financial markets we have today. We owe much of this advancement to the evolutionary mechanism of Darwinian natural selection, and, according to Edmund T. Rolls' 1999 study "On the Brain and Emotion," humans can thank our often irrational emotions for the progression of our species. Emotions are often described as a limitation on human potential, but they actually lend vital decision-making support. They make us human, and provide crucial feedback about the environment and past choices. Emotions help us make reward-and-punishment decisions, which is beneficial from an evolutionary perspective. In financial decisions, people may behave with strong emotions like greed, fear, and exuberance, which would seemingly prevent market efficiency. However, in his work "The Efficient Markets Hypothesis and Its Critics," Burton Malkiel asserts that markets can be efficient even if many participants are irrational. He explains that as long as these participants cannot earn above-average risk-adjusted returns. While the Efficient Markets Hypothesis (EMH) may still be valid with irrational participants, questions may arise about the validity of the hypothesis due to the emotional nature of market participants. Meanwhile, Robert J. Shiller argues in, "From Efficient Markets Theory to Behavioral Finance," that market anomalies often disappear. The existence of these temporary anomalies, usually patterns, suggests that markets do not act rationally and efficiently. Considering this discrepancy, it is important to study the effects emotion may have on market efficiency. This study builds on research by Paul Beaudry, Deokwoo Nam, and Jian

Wang (2011), which found evidence that emotion drives the business cycle.

The business cycle is a normal, perpetual cycle of expansions and contractions, and must be considered in determining the validity of the EMH. Using the research of Beaudry, Nam, and Wang, and assuming emotions drive expansions and contractions, market efficiency may deviate in different parts of the cycle. Considering the above questions and making the assumption that the U.S. stock market is reasonably efficient, this paper will discuss the U.S. business cycle and its potential effects on the EMH in the U.S. stock market. The purpose of this paper is to test the efficiency of the U.S. stock market, using the CAPM, during expansions and contractions of the business cycle from 1927 to 2009. This research is important because many pricing models assume efficiency. These models are depended on, directly or indirectly, by most market participants. When these models fail, like they did in 2008, a lot of investors can be harmed.

## **The EMH**

The EMH is arguably the most influential hypothesis in modern financial theory. Informing investment and management decisions, the EMH has been a cornerstone of financial thinking since 1970. Eugene Fama compiled empirical evidence at that time that supported the EMH and described it as “informationally efficient.” That is, securities prices are accurate reflections of all available information. This definition has two significant implications.

First, when all available information is accurately reflected in a security price, attempting to “beat the market” is a waste of effort because, in a perfectly efficient market, it is impossible to obtain above market returns without taking above market risks. In this scenario, the intrinsic value of a stock is equal to its market value ( $P_0 = \hat{P}_0$ ), and the required return of a stock is equal to its expected return ( $r_s = \hat{r}_s$ ). So, for the stock market to be in perfect equilibrium, the mean of all perceptions of the stock market’s value would have to equal the

real value of the stock market. Considering the irrational behavior of market participants, it would seem unlikely that the stock market is consistently in equilibrium. However, we should consider the statistical concept of the “wisdom of the crowd.” This is when the mean of the group is “wiser” than the individual. Considering this notion, it may be possible that the mean perception of market value could equal its true value when irrational participants are involved. This also validates Malkiel’s belief that irrational participants do not prevent an efficient market. Furthermore, authors Michael C. Ehrhardt and Eugene F. Brigham agree that the market seems to be “reasonably efficient in the sense that the intrinsic price is approximately equal to the actual market price ( $P_0 \approx \hat{P}_0$ ),” explaining that experienced investors act quickly when  $P_0 \neq \hat{P}_0$ , which forces the market back to equilibrium. Malkiel asserts that traders may *occasionally* achieve “above-average risk-adjusted returns” by selling overvalued stocks and buying undervalued stocks immediately. However, Malkiel explains that short-term gains are often negated by long run mean reversion, and transactions costs which is consistent with the EMH. Considering these points, it seems reasonable that the market cannot be *consistently* beaten.

News is random, so the second aspect of efficiency implies that the stock market is unpredictable. If securities prices reflect all information, all of the news in a particular day is reflected immediately. The following day’s price would then be independent of the news from the day before, and would only reflect that current day’s news. This means that it is irrational to expect a company’s stock to increase or decrease on day two because it increased or decreased during day one. With no way of accurately predicating random events, it would be impossible to predict security prices. This means neither technical analysis nor fundamental analysis would be useful for investors. The existence of a price pattern does not contradict the EMH for a few reasons. In an efficient market, according to Malkiel, any profitable price pattern that may exist will not survive. Some patterns do not actually exist, but are believed to exist because of biases

and misidentification. Real patterns are rarely reliable, making them relatively unpredictable and, therefore, efficient. The January Effect, Monday Effect, and others have been proven to be too unreliable and too unpredictable to be called patterns. Lastly, when a pattern is known, investors tend to exploit it to death, which brings the market to equilibrium. Under the EMH, an amateur investor could randomly select a portfolio of securities and achieve the same return as a professional compiling a portfolio with equal risk to the random portfolio. Historically, this seems to be true as the average fund return has only outperformed the market six times in the last twenty years. More evidence of market efficiency is that the average alpha of mutual funds is -1.25, which indicates the excess return from what should have been obtained considering the fund's beta.

The definition of the EMH includes three forms of market efficiency: strong-form, semi strong-form, and weak-form. The strong form describes a market where all available information is already reflected in prices. In this form, the sum of all public and private knowledge is already reflected. This means that even insider trading is futile because private information is already a part of the current price. In this form, markets are entirely unpredictable because daily news is immediately included in prices. A semi-strong form of market efficiency exists if all public information is already reflected in prices. The weak-form of market efficiency describes a market where past prices are included in present prices. This means fundamental analysis is the only meaningful type of analysis. These forms are imperfect and can be easily critiqued.

Consider the following paradox of strong-form market efficiency. If the market was informationally efficient, no one would waste time trying to earn above market returns. Yet, fund managers are paid very well to outperform the market. Many investors are motivated by

achieving what the strong form of the EMH says should not happen. Furthermore, watchdogs would have no reason to exist because insider trading and other comparable schemes would be fruitless for investors. In reality, insider traders have been profitable. Ivan Boesky, for instance, infamously earned about \$50 million from insider trading in 1985. Short-and-distort and pump-and-dump market manipulation schemes, where the goal is flooding the market with information, would be impossible because all information is already included. Traders would have nothing to gain from illegal trading practices, and companies would have no incentive to report financials unethically. If all private information is already reflected in a stock price, a company would have nothing to gain from presenting untrue financial statements because the actual numbers would be included in the price.

The semi-strong form of efficiency means that information provided in annual reports is meaningless for understanding prices because that information was already reflected in the price. So, fundamental analysis is useless because all information that could be derived from these techniques is already reflected in the price. Investors can expect returns found by the CAPM, but no more and no less. In reality, the CAPM is an imperfect model, and fundamental techniques can be rewarding.

Fundamental analysis is meaningful in the weak form of market efficiency because it says past prices are reflected in the current price. Company financials, key ratios, and qualitative economic factors are all important in determining the intrinsic value of a stock. Ehrhardt and Brigham assert that, while still inconclusive, empirical evidence strongly supports weak-form efficiency. The semi-strong form is reasonably supported. Strong-form efficiency has very little support considering its issues listed above. This research assumes weak-form efficiency.

## The CAPM

The CAPM analyzes risk and rates of return with the idea that risk and the time value of money have to be accounted for. The model finds the expected return ( $\hat{r}_s$ ) of a security by adding the risk-free rate ( $r_f$ ) to the product of the security's beta ( $\beta_s$ ) and the market risk premium ( $r_m - r_f$ ), where  $r_m$  is the required market return. The risk-free rate is generally the rate on ten-year Treasury Bonds because stocks are typically held as long-term investments, and these T-bonds are less volatile than short-term T-bills.

$$\hat{r}_s = r_f + \beta_s(r_m - r_f)$$

The CAPM is the most commonly used asset pricing model. In fact, about 74% of firms use the CAPM, and academics frequently use it for research. Yet, this model is imperfect. The variables are expected values from historical data, rather than true reflections of future expectations. The realized returns of the past may not equal the expected returns of the future. The beta coefficient is also calculated from past information, with the assumption that it will stay about the same in the future. Robert Levy found in his study, "On the Short-Term Stationarity of Beta Coefficients," that individual stock betas are very unstable, but betas tend to be more stable in portfolios with more than ten stocks. So, using CAPM for individual stocks may give less accurate returns. During this research I used betas of mutual funds and ETFs with more than ten holdings. Other limiting assumptions of the CAPM include no transactions costs, no taxes, and all investors have the same expectations.

The bottom line of using the CAPM is that it is an example of a GIGO (garbage in, garbage out) computation. It is only as good as its inputs. The sample of historic data used to find its variables greatly impacts the expected return. Considering this, the CAPM's results can be erroneous and create irrational expectations. The CAPM is widely used, and it is rational on a

theoretical level. Yet, its limitations, especially when not recognized by its users, inject a substantial amount of Knightian uncertainty.<sup>1</sup> Its limitations, especially with beta calculations, make computing the true risk difficult. It is reasonable to assert that, to an extent, what we call risk is actually more of uncertainty. Considering the scope of its use, our expectations may be less rational and our calculations may be less certain when using the CAPM.

### **The Business Cycle**

The business cycle moves from an expansion to a peak, followed by a contraction to a trough. According to the National Bureau of Economic Research (NBER), fourteen cycles have occurred since 1927 (Table 1). Traditionally, a recession is defined by six or more months of economic decline. The NBER measures recessions as a “significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales,” and this definition will be used throughout this paper. The business cycle is a normal process, but the cause is uncertain. The aforementioned 2011 NBER working paper by Beaudry, Nam, and Wang, titled, “Do Mood Swings Drive Business Cycles and is it Rational?”, concluded that optimism and pessimism are the driving forces of business cycles. The methodology of the study consisted of isolating changes in optimism and pessimism by analyzing the variance in the maximum forecasts for each period. Ehrhardt and Brigham also assert that risk aversion changes based on our environment by explaining that market risk premiums reached high levels during the 2007-2009 recession because participants wanted to be compensated more for the risk. The business cycle is a random but normal and expected process of an economy, which still fits our definition

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<sup>1</sup> From Frank Knight’s *Risk, Uncertainty, and Profit* that essentially defines risk as calculable, and uncertainty as not calculable.

of efficiency. Considering the emotion nature of all participants and the conclusion of this research, this paper assumes the conclusion of the above study is reasonable.

Peak Month	Trough Month	Length of Contraction (months)	Length of Expansion (months)	Period of Cycle-To Trough From Previous Trough (months)
October 1926	November 1927	13	27	40
August 1929	March 1933	43	21	64
May 1937	June 1938	13	50	63
February 1945	October 1945	8	80	88
November 1948	October 1949	11	37	48
July 1953	May 1954	10	45	55
August 1957	April 1958	8	39	47
April 1960	February 1961	10	24	34
December 1969	November 1970	11	106	117
November 1973	March 1975	16	36	52
January 1980	July 1980	6	58	64
July 1981	November 1982	16	12	28
July 1990	March 1991	8	92	100
March 2001	November 2001	8	120	128
December 2007	June 2009	18	73	91

**Table 1: The recession length is calculated by time from peak to trough. The expansion is the difference between the previous trough month and the current peak month. Cycle length from trough to trough can be found with the difference between the trough month/year and the trough month/ year**

## Methodology

Summarizing the above concepts, this research is performed under empirically supported assumptions: the stock market is efficient in the weak-form, and optimism and pessimism drive the business cycle. The remainder of this research, with data from 1927 to 2009, will seek to determine the efficiency in the stock market during different parts of the business cycle. This will require compiling market returns and comparing them to the returns of a sample of mutual funds and ETFs that closely follow the market. These comparisons will be made during different parts of the business cycle.

The methodology for testing market efficiency during contractions and expansions of various business cycles has five steps. First, using NBER business cycle data, each of the fourteen cycles from 1927 to 2009 will be investigated. Second, monthly stock market returns will be collected during each contraction and expansion of the identified cycles. Returns for the S&P 500 provided by Robert J. Shiller will be used for a benchmark.<sup>2</sup> I decided to use the S&P data, as opposed to other benchmarks, because of its large sample that represents the overall market. Then, the market returns will be compared to returns of various mutual funds and ETFs, which were adjusted for dividends and stock splits. The returns of a sample of funds and ETFs that simulate the market benchmark closely will be compared to the market's returns. The sample is limited to funds and ETFs with long-term historical betas under 1.0 (Table 2).

Fund/ ETF	VTSMX (fund)	SWTSX (fund)	IWV (ETF)	WFIVX (fund)	PINVX (fund)
Summary	Large-cap blend that tracks the total return of the entire U.S. stock market.	Large-cap blend that tracks the total return of the entire U.S. stock market.	Large-cap blend that tracks the Russell 3000® Index.	Large-cap blend that tracks the Wilshire 5000 IndexSM.	Large-cap blend that seeks capital growth.
Inception Date	Apr 27, 1992	Jun 1, 1999	May 22, 2000	Jan 29, 1999	Dec 1, 1925
Long-term Beta	0.779	0.782	0.831	0.787	0.810

Table 2: The inception date is the date the fund or ETF was started. The long-term beta was computed using all of the fund or ETF's monthly returns.

<sup>2</sup> Shiller uses S&P four-quarter totals since 1926, with linear interpolation to monthly values to compute earnings.

According to the EMH, an investor cannot “beat the market” with below average risk. Choosing funds and ETFs with betas less than 1.0 gives the expectation that volatility, or risk, will be below that of the stock market. So, if the returns are greater than the stock market, it may weaken the EMH. Next, the CAPM will be used to control for risk, which will require using the beta of the fund or ETF. During this research, I computed the beta coefficient by taking the covariance of the sample’s and market’s returns and dividing by the variance of the market’s returns. I computed a long-term beta (from the inception date to 2009) and a beta for each expansion and contraction. Determining the excess return will require multiplying the beta by the market’s return and subtracting the fund or ETF’s return. I will determine monthly returns for the fund or ETF and the market. Following the computation of excess returns, I will calculate the average return from the sample and determine a standard error. The final step of my research is to find the statistical significance. If this procedure returns values that are statistically significant, it may mean that the particular part of the business cycle that the data was pulled from affected returns possibly by either generating irrational optimism or pessimism depending on the sign of the value.

### **Hypothesis**

With support from Malkiel and Ehrhardt and Brigham, I suspect the U.S. stock market will show strong long- term efficiency because of evidence of mean reversion and price reversals. I do not expect any anomalous returns in the long-term because the market will likely not allow these returns to persist for a long time. I expect reasonable efficiency in the short-term because I suspect the market is inefficient during overly optimistic periods (expansion) and overly pessimistic periods (contraction). In the long-term and short-term:

$$H_0: \mu = 0$$

$$H_1: \mu > 0$$

## Results

First, I compared the returns during each expansion and contraction while aggregating the returns of the funds (Table 3). I also investigated the beta of each fund or ETF during each part of the cycle, to see if the cycle drives volatility (Table 4). After compiling the returns and adjusting for market performance and risk, I could estimate the t-statistic and p-value for the returns of each fund and ETF for expansions and contractions (Table 5), and the whole sample (Table 6).

<b>All Expansions 1927-2009</b>			
<i>S &amp; P</i>		<i>All Funds</i>	
Mean	4.66%	Mean	0.67%
Standard Error	0.13%	Standard Error	0.14%
Median	4.58%	Median	1.11%
Standard Deviation	3.86%	Standard Deviation	4.83%
Sample Variance	0.001488	Sample Variance	0.002334
Skewness	-0.15888	Skewness	-0.29994
Minimum	-9.44%	Minimum	-22.06%
Maximum	22.44%	Maximum	27.46%
<b>All Contractions 1927-2009</b>			
<i>S &amp; P</i>		<i>All Funds</i>	
Mean	4.38%	Mean	-0.63%
Standard Error	0.52%	Standard Error	0.54%
Median	5.91%	Median	0.11%
Standard Deviation	6.93%	Standard Deviation	8.86%
Sample Variance	0.004796	Sample Variance	0.007858
Skewness	-0.58357	Skewness	0.986179
Minimum	-23.04%	Minimum	-37.44%
Maximum	26.87%	Maximum	56.15%

Table 3: The aggregated returns of all the funds compared to the returns of the benchmark over the same period.

The data above show that the funds in the sample had an average return of 0.67% during expansions, compared to the benchmark's 4.66% average return. This suggests market efficiency because the return is below the market's return. The returns for the funds had a higher maximum value, but could not consistently outperform the market. During contractions, the funds had an average return of -0.63%. The market had an average return of 4.38%, which was similar to its return during expansions. Average returns for the market and the sample during expansions changed only slightly from contractions, suggesting the cycle does not have a great effect on market returns. The major difference was the standard deviation. The standard deviations for the returns of both the market and the funds nearly doubled during contractions. This may suggest that changes the cycle drive some volatility, but probably do not affect overall efficiency.

The following data in Table 3 examines the beta coefficient of each fund or ETF during each part of the business cycle, since its inception.

Beta During Expansions		Beta During Contractions	
PINVX		PINVX	
Mean	0.84	Mean	0.83
Standard Deviation	0.32	Standard Deviation	0.30
Maximum	1.74	Maximum	1.36
Minimum	0.36	Minimum	-0.01
VTSMX		VTSMX	
Mean	0.75	Mean	0.80
Standard Deviation	0.06	Standard Deviation	0.02
Maximum	0.81	Maximum	0.82
Minimum	0.69	Minimum	0.77
SWTSX		SWTSX	
Mean	0.72	Mean	0.79
Standard Deviation	0.08	Standard Deviation	0.02
Maximum	0.80	Maximum	0.80
Minimum	0.63	Minimum	0.77
IWV		IWV	
Mean	0.85	Mean	0.80
Standard Deviation	0.03	Standard Deviation	0.05
Maximum	0.88	Maximum	0.75
Minimum	0.81	Minimum	0.85
WFIVX		WFIVX	
Mean	0.74	Mean	0.78
Standard Deviation	0.07	Standard Deviation	0.02
Maximum	0.81	Maximum	0.76
Minimum	0.67	Minimum	0.80

Table 4: The average, standard deviation, maximum, and minimum values of the beta coefficient during each expansion and contraction.

The beta, on average, is about the same during expansions and contractions. The standard deviation for each fund or ETF did not drastically change between expansions or contractions. The difference between an expansion beta and the following contraction beta was also small. The average difference in the sample's beta between an expansion the immediate contraction was 2%. Conversely, the difference between a contraction beta and the immediate expansion was 3%. So, the betas of the funds and ETFs in this sample were not significantly altered by changes in the business cycle.

Next, I examined the t-statistic of the excess returns. I analyzed the excess returns of each fund during each period of the cycle (Table 4), and the aggregate excess returns of each cycle to help determine market efficiency during each part of the cycle (Table 5). The distributions of returns for each fund or ETF and the overall sample are in Appendix A. The results lend no evidence that the market is less efficient during contractions or expansions in the long-term or short-term.

Returns for Funds During Expansions Using Long Term Beta		
Fund/ETF	T-Statistic	P-Value
VTSMX	-4.85513	0.93530
SWTSX	-1.94657	0.15110
IWV	-1.65368	0.82690
WFIVX	-2.32086	0.87050
PINVX	-6.31026	0.99999
Returns for Funds During Contractions Using Long Term Beta		
Fund/ETF	T-Statistic	P-Value
VTSMX	-1.57567	0.82000
SWTSX	-2.67311	0.88600
IWV	-2.85194	0.89270
WFIVX	-2.64589	0.88500
PINVX	-1.23858	0.88210
Returns for Funds During Expansions Using Short Term Beta		
Fund/ETF	T-Statistic	P-Value
VTSMX	1.48922	0.18820
SWTSX	-1.80202	0.83870
IWV	-1.65472	0.82700
WFIVX	-2.09984	0.85850
PINVX	-5.67402	0.99999
Returns for Funds During Contractions Using Short Term Beta		
Fund/ETF	T-Statistic	P-Value
VTSMX	-1.43590	0.80640
SWTSX	-2.48434	0.87820
IWV	-2.73765	0.88850
WFIVX	-2.60703	0.88340
PINVX	-1.08030	0.85090

Table 5: T-Statistic and P-Value for each fund/ETF during expansions and contractions using a long-term and short-term beta.

<b>Aggregate Returns During Expansions Using Long Term Beta</b>	
T-Statistic	P-Value
-6.66376	0.99999
<b>Aggregate Returns During Contractions Using Long Term Beta</b>	
T-Statistic	P-Value
-2.15260	0.97870
<b>Aggregate Returns During Expansions Using Short Term Beta</b>	
T-Statistic	P-Value
-4.58585	0.99992
<b>Aggregate Returns During Contractions Using Short Term Beta</b>	
T-Statistic	P-Value
-1.10584	0.85960

Table 6: The T-Statistic and P-Value for the returns of the whole sample during expansions and contractions.

## Conclusion

The purpose of this research was to determine if the business cycle affects market efficiency. I made two assumptions during this research: market efficiency exists in the weak-form and emotion drives the business cycle. This study was limited by the availability of historical data to compare to the benchmark. Creating a larger, more diverse sample could create more significant results. The results are also limited by the CAPM because it's imperfect, and betas can be calculated a variety of ways. Applying more than one model could lend more insight into market efficiency. My sample may also contain some error because I could not account for transactions costs or taxes, and it likely contains some survivorship bias.

After analyzing the returns of the stock market and the aggregate returns of the sample, using long-term and short-term betas, I found that there is no evidence that expansions or contractions drive inefficiency (Table 6). I fail to reject the null hypothesis that the sample's returns, controlled for risk, will be equal to the market's returns. I reject the alternative

hypothesis that the sample's returns will be greater than the market's returns. The implication of this conclusion is that it is unlikely that the business cycle causes inefficiency in the U.S. stock market. This conclusion supports the EMH because it should be impossible to gain above-average returns with below-average risk. It is possible that the business cycle used to drive inefficiency in the stock market and, like most patterns, it was exploited by investors. This pattern, if it ever existed, would probably already be exploited into extinction. After analyzing the beta coefficient during each contraction and expansion, there is little evidence that the business cycle significantly affects betas (Table 4). The change from an expansion to a contraction and a contraction to an expansion did not create a significant change in the sample's betas. This strengthens Levy's findings on the stability of betas in portfolios of over ten holdings. Interestingly, returns during contractions had higher standard deviations than the returns during expansions (Table 3). This suggests that contractions may create more volatility than expansions. This is interesting because the average returns during expansions were still higher than the more volatile contractions. Further research may investigate this discrepancy. Perhaps historical alpha values will be studied during each expansions and contractions to gauge changes in excess returns.

Finance and economics are arts. These fields do not have the luxury of exact laws that can be applied when modeling most situations. Many formulas contain a degree of uncertainty, and even commonly used equations, like the CAPM, cannot be exact. As sciences, these fields are more comparable to meteorology than physics, considering the challenges of modeling human nature. This is why testing the EMH is so crucial. The EMH, which is strengthened by this research, lends some clarity to these imperfect models, but it is not enough. Future research is needed to thoroughly examine the EMH and financial models.

In further research of efficiency, the degree of asymmetrical information reflected in prices may be explored. Currently, the EMH requires some asymmetrical information. For instance, as soon as news is released many institutional investors are immediately notified (usually well before the typical investor reads about it in the paper in the next day), and can act on it. Computers can react to news within a second, but by the time most typical investors can act, the news is already reflected in the price. While the same information is available to all participants, not all participants have equal ability to act on the information, so asymmetry ipso facto exists in the current system. This scenario also assumes that all participants have the same knowledge of investing, which appears to be untrue.

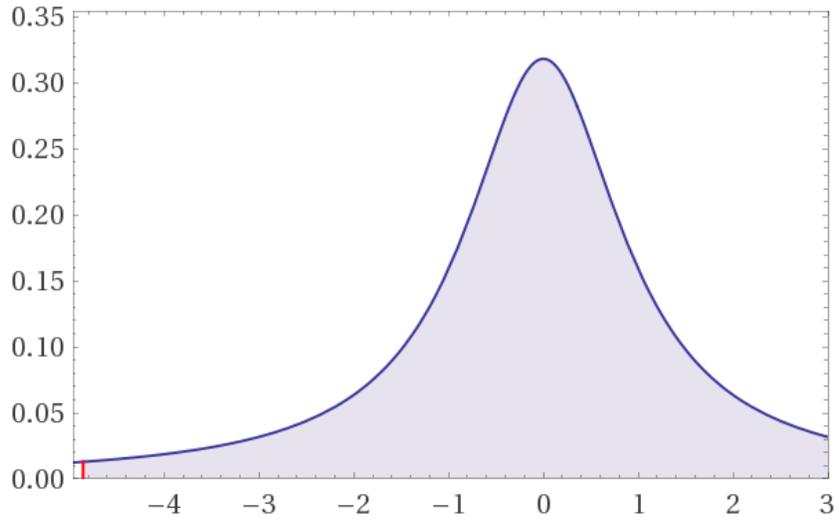
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## Appendix A

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

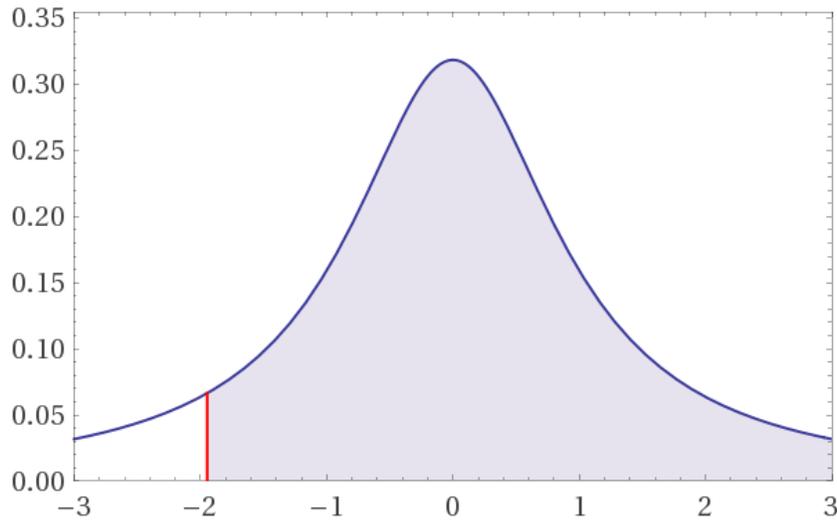


Computed by Wolfram|Alpha

**VTSMX long-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

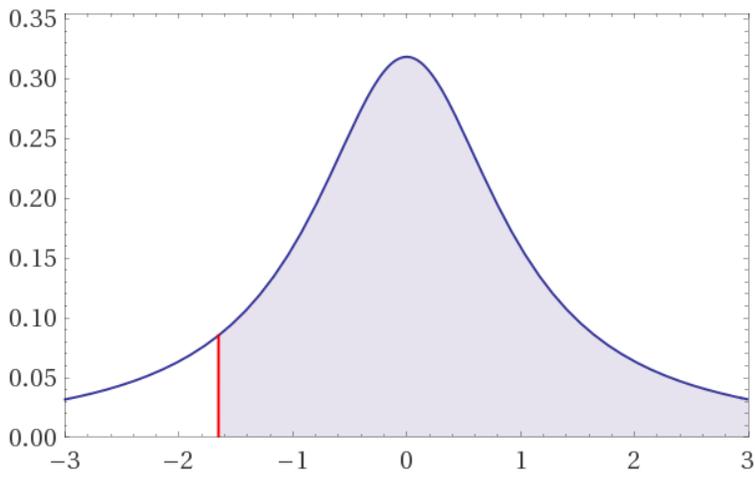


Computed by Wolfram|Alpha

**SWTSX long-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

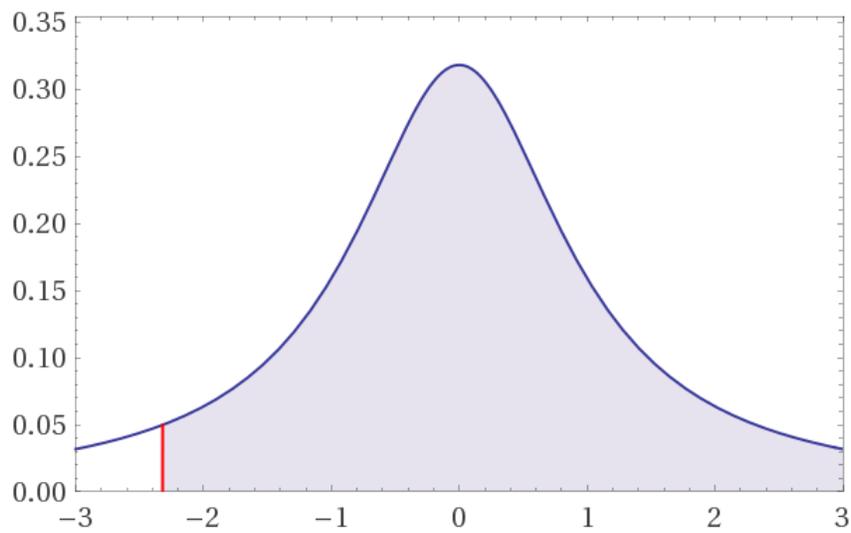


Computed by Wolfram|Alpha

**IWV long-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

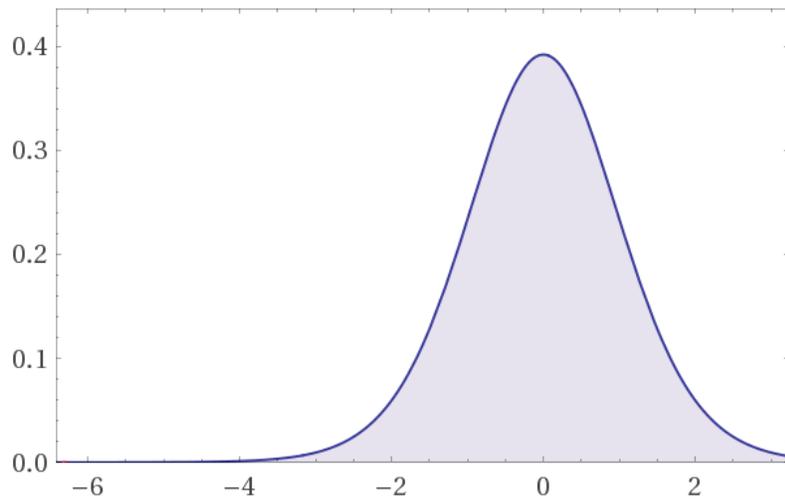


Computed by Wolfram|Alpha

**WFIVX long-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

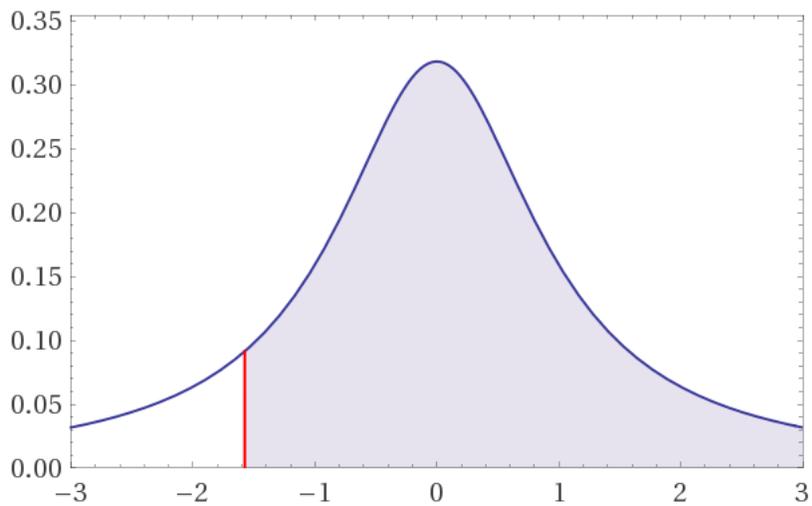


Computed by Wolfram|Alpha

**PINVX long-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

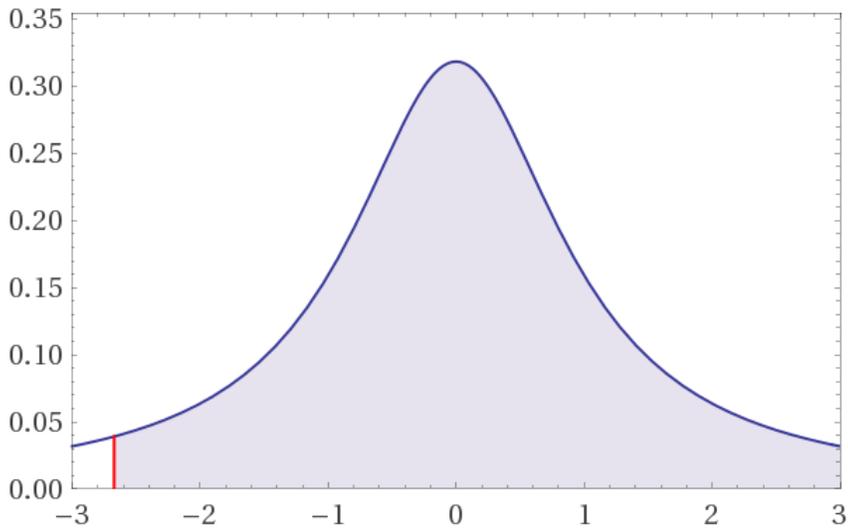


Computed by Wolfram|Alpha

**VTSMX long-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

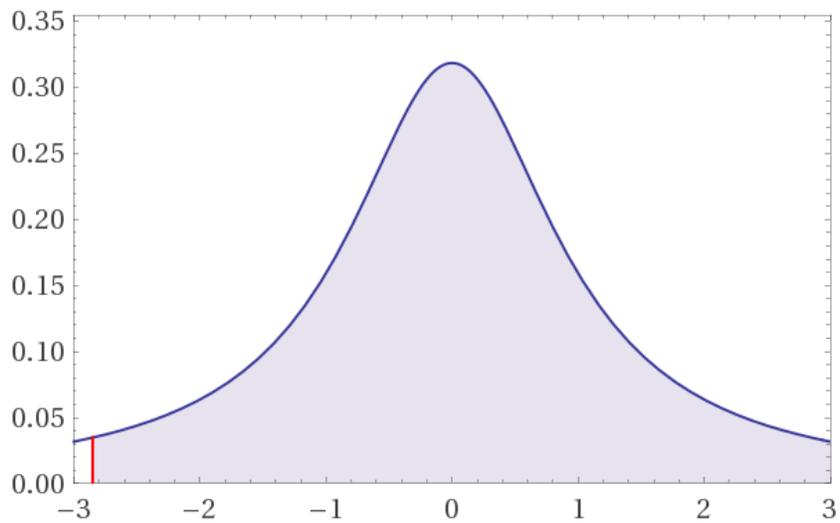


Computed by Wolfram|Alpha

**SWTSX long-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

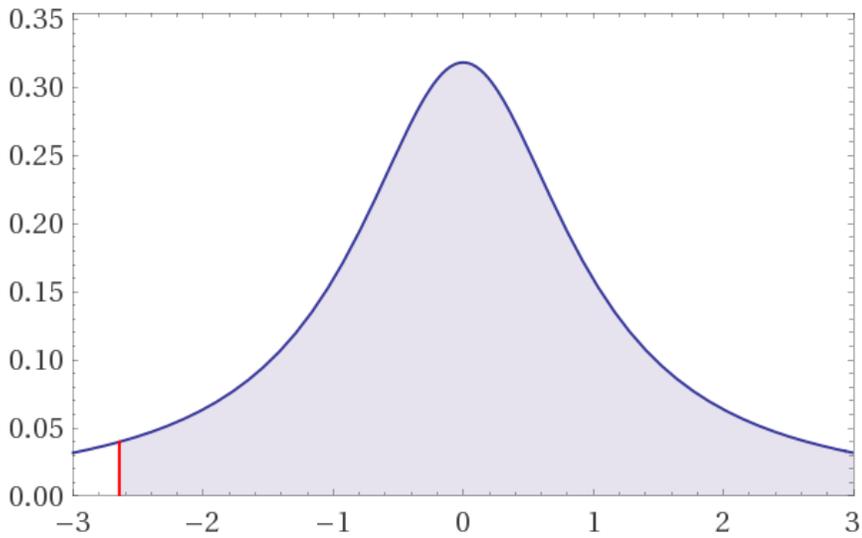


Computed by Wolfram|Alpha

**IWV long-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

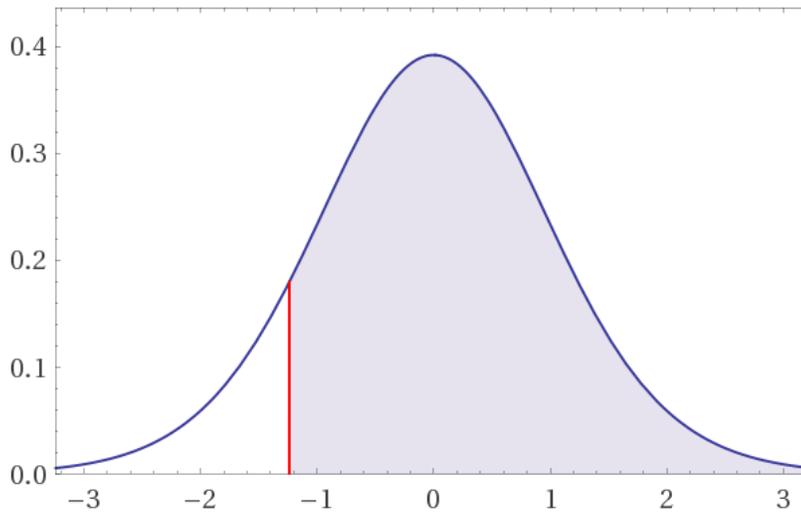


Computed by Wolfram|Alpha

WIVFX long-term beta return distribution during contractions.

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

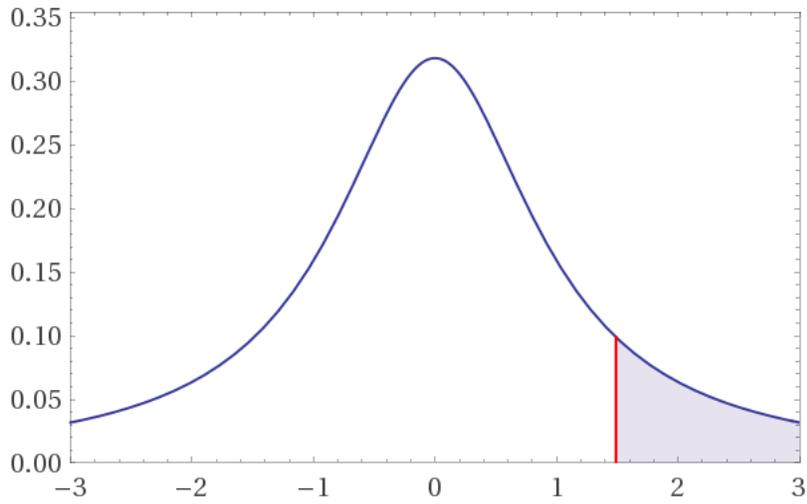


Computed by Wolfram|Alpha

WIVFX long-term beta return distribution during contractions.

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

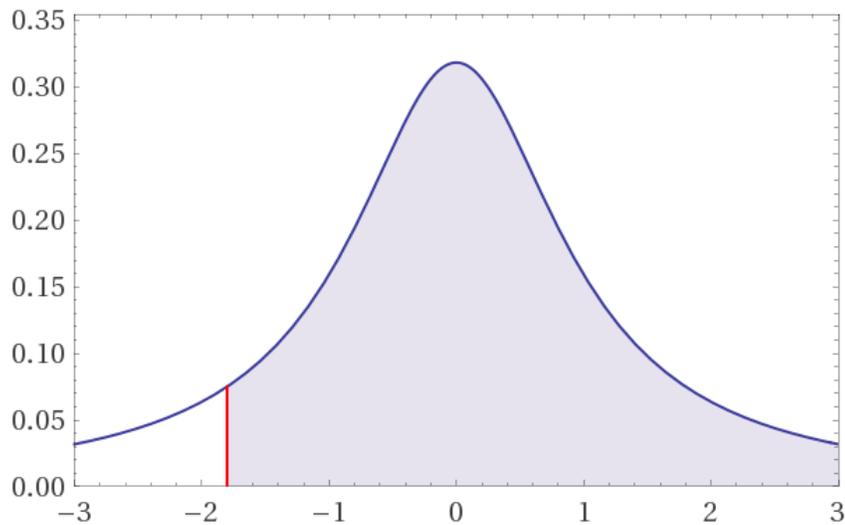


Computed by Wolfram|Alpha

**VTSMX short-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

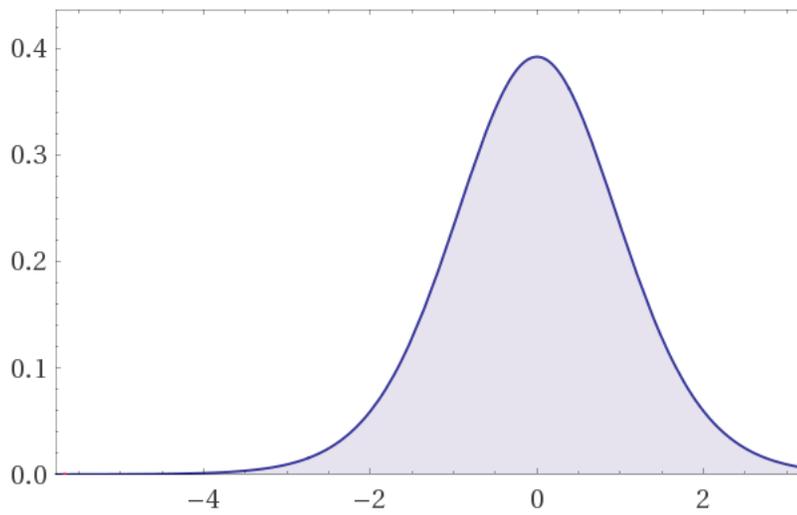


Computed by Wolfram|Alpha

**WFIVX short-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

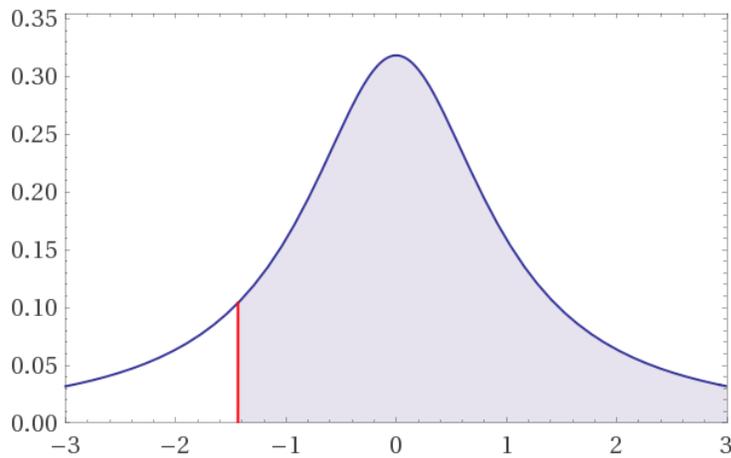


Computed by Wolfram|Alpha

**PINVX short-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

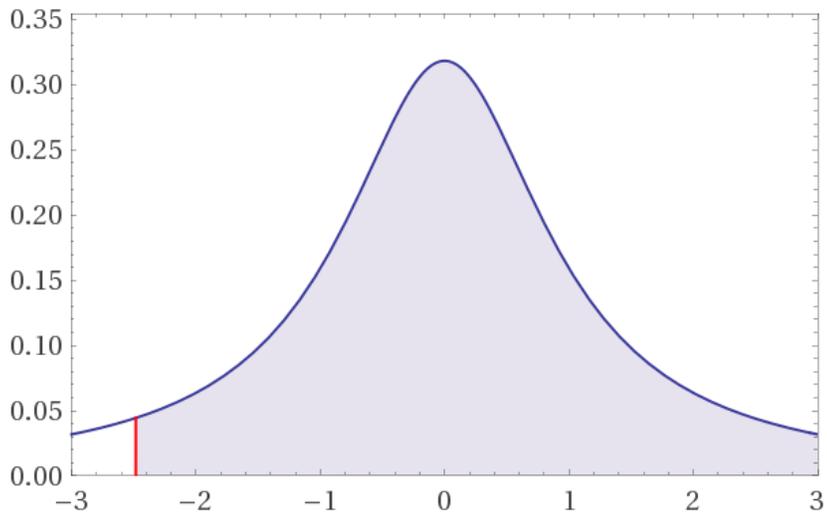


Computed by Wolfram|Alpha

**VTSMX short-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

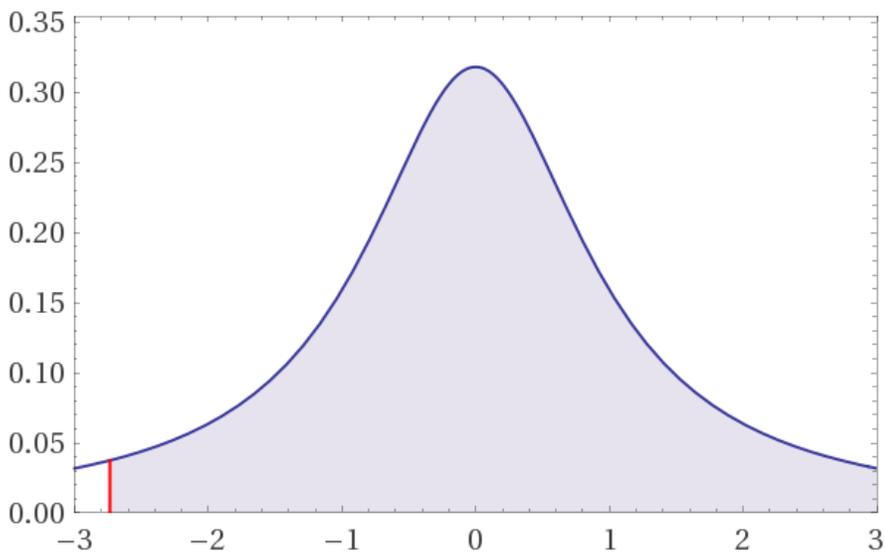


Computed by Wolfram|Alpha

SWTSX short-term beta return distribution during contractions.

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

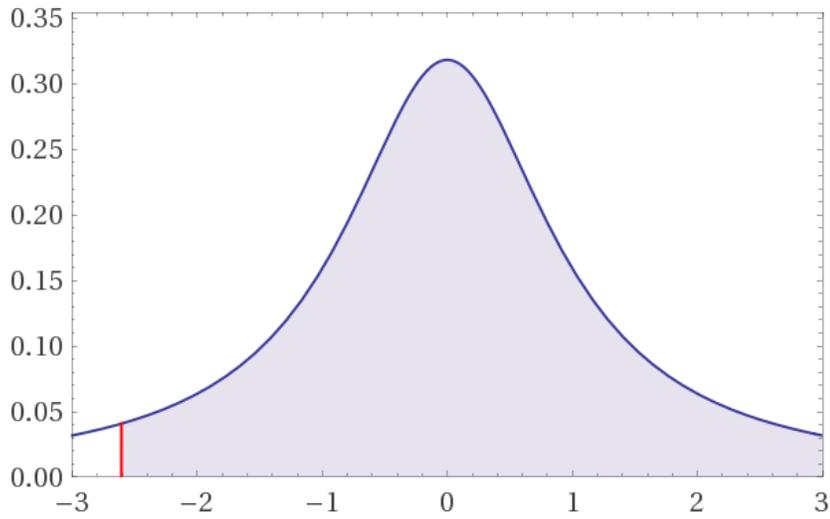


Computed by Wolfram|Alpha

IWV short-term beta return distribution during contractions.

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

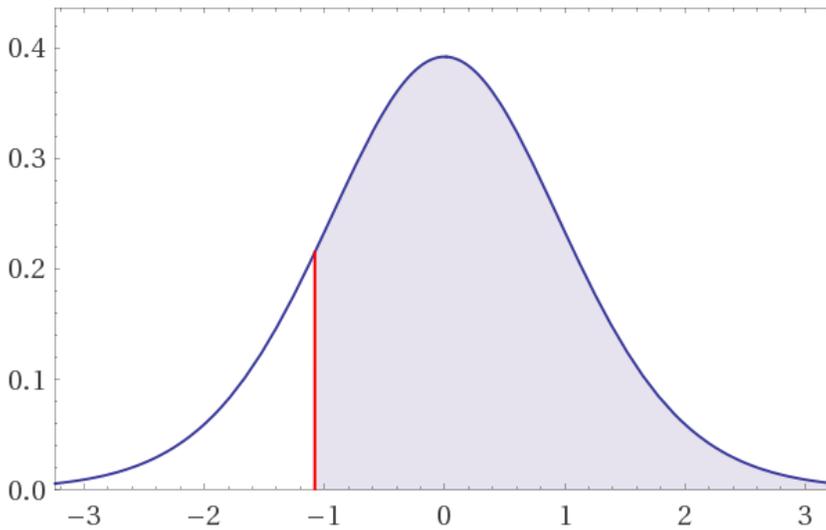


Computed by Wolfram|Alpha

**WFIVX short-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

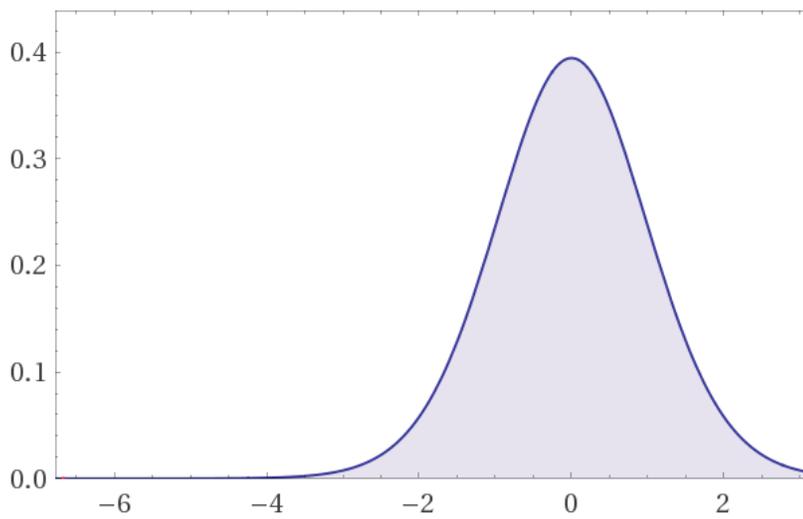


Computed by Wolfram|Alpha

**PINVX short-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

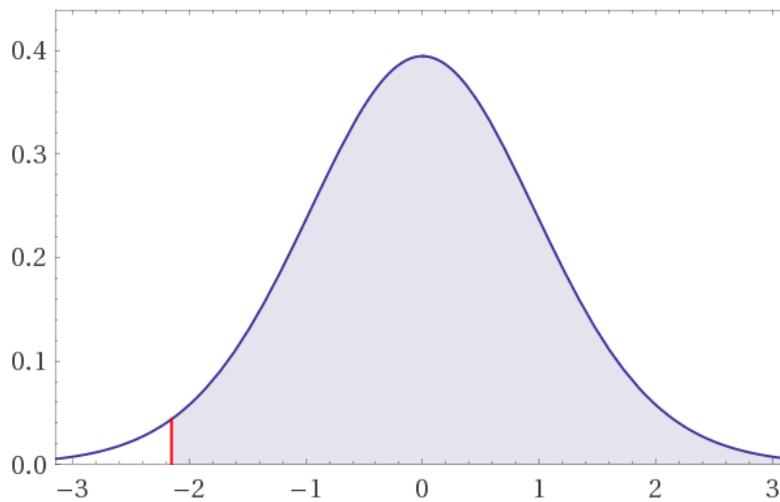


Computed by Wolfram|Alpha

**Aggregate long-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

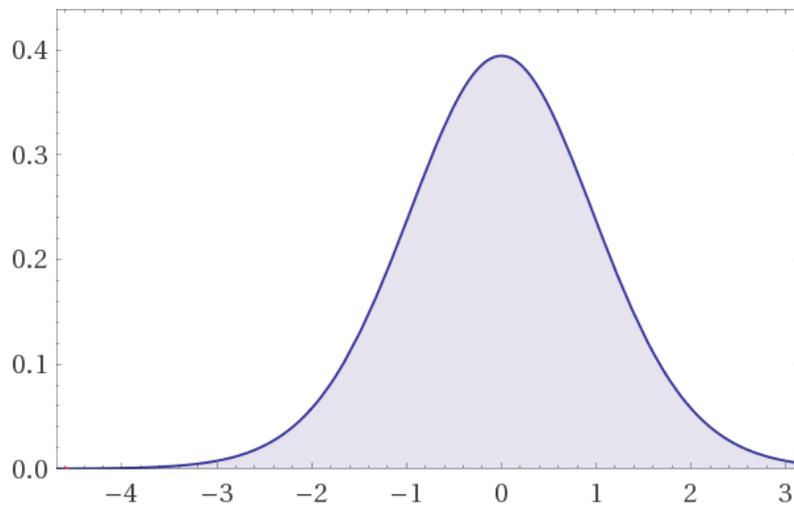


Computed by Wolfram|Alpha

**Aggregate long-term beta return distribution during contractions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :

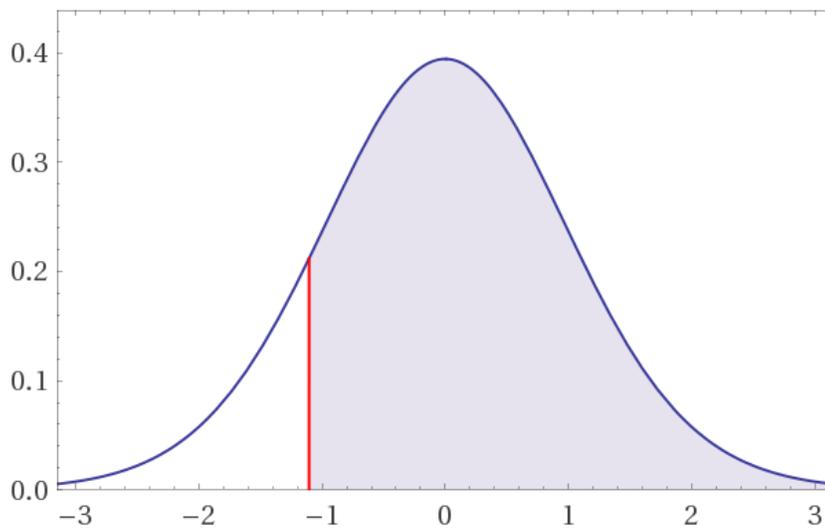


Computed by Wolfram|Alpha

**Aggregate short-term beta return distribution during expansions.**

Right-tailed test :

Sampling distribution of test statistic under the null hypothesis :



Computed by Wolfram|Alpha

**Aggregate short-term beta return distribution during contractions.**