A Case for Volatility-Based Technical Analysis

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Abstract

Actively managed portfolios have struggled in recent years. Traditional information flows have failed to provide the edge necessary for desired risk adjusted returns. Fortunately, the methodology shown herein is a quantitatively viable advantage, which can be algorithmically applied.

Funds and institutions struggle to execute due diligence processes around trading and portfolio management. With these time constraints forecasting price behavior is ever more difficult.

Northington Dahlberg Research provides an innovative method to forward project price level turning points days, and often weeks, in advance. Volatility-Based Support Resistance (VBSR) is an emerging methodology which is supported by statistically viable quantitative results. Its implementation can greatly improve portfolio planning, risk management and trade execution.

This paper will explain the practice and theory of VBSR. Additionally, practical market based evidence is presented to explain why VBSR is effective.

Introduction

Favorable risk adjusted returns can be, at times, as difficult to attain as a porcupine in a balloon factory. Forces are constantly at work to ensure that neither of these occur. What follows will outline an emerging solution for forecasting technical price and volatility value levels. The solution is termed Volatility-Based Support Resistance (VBSR).

You will be able to understand how VBSR enables risk analysts, portfolio managers, and trading execution teams to more accurately forecast best price levels for accumulation. Additionally, light will be shed on identifying points where market implied volatility can be forecasted to alter its prevailing directional track.

Proper risk governance & oversight mandates that we execute careful processes for selecting opportunities. Steps to include macro market influences, investment mandates, and price/value forecasting involve multiple groups in the decision framework. Processes consume time, and cause opportunities to be missed. Time, not unlike confirmation, consumes Alpha. How can we execute due diligence yet still be quick enough?

Historical

A common question asked is why are market opportunities so fleeting; gone almost as soon as they are recognized? Why is this problem getting more difficult? Perhaps this is because there are currently greater levels of artificial market manipulation.

In the most recent 10 to 15 years our largest global financial institutions have been increasingly mandated to tightly control risk. This occurs most largely through the use of derivatives. In 2001 the world's largest Globally Systemically Important Banks (G-SIBs) controlled 57% of all financial assets[1].

Since the recent 2008 financial crash G-SIBs are tightly regulated by an increasing quantity of risk models which mandate capital constraints on a daily basis. The two largest mathematical inputs to risk models are historical and implied volatility. More than half of all financial assets held are subjected to rebalancing in OTC and exchange traded markets daily.

These models rarely consider the price of an asset, or its price momentum in any form. The models are largely based on volatility data; of which financial institutions must procure and download each evening. The budgets to purchase market implied and historical volatility data have ballooned in recent years, and show no sign of slowing.

These external mathematical and computational models are at the heart of the market's microstructure. They have made it increasingly inaccurate to forecast security prices base on linear measurements, or momentum calculations. The non-linear relationship of implied volatility to price direction has diminished the utility of the venerable trend line; and other linear analysis techniques.

Innovation

To illustrate this difficulty, consider that the firm's macro research issues its opinion favoring a specific sector. The sector is considered a value play and has begun an initial move up from an extended downtrend. Next comes the common activity of building a sizable long position in a basket of stocks. Time is required to accumulate within the market's liquidity constraints.

The research process has already consumed time. The confirming initial move up has cost Alpha, and more time. It's at this point that critical decisions must be made. Have individual basket constituent stocks risen too far? Should execution anticipate short term profit taking? Is the sector's value obvious to most of the market and thus will prices run and not look back?

As the psychologist say, "how you deal with this issue, *is* the issue". The challenge is simpler with the right approach. Are the stocks, individually and collectively, at resistance? More importantly are they at resistance as defined by volatility measurement?

Volatility-Based Support & Resistance (VBSR), uses previous volatility extremes to identify price levels which form probable future support or resistance. This enables trade execution to measure the stock price distance to resistance; the point where supply will overtake demand.

In Figure 1.1 a daily candle chart of Netflix Inc. (NFLX :NASDAQ) shows VBSR plotted along with a 50 day simple moving average. A blue arrow depicts an algorithmically generated support condition occurring at the lower support zone. The chart's history show's a varied with the 50 day moving average; a common momentum support indication. Figure 1.2 completes the statistical averaged price behavior as a reversal and trend continuation.

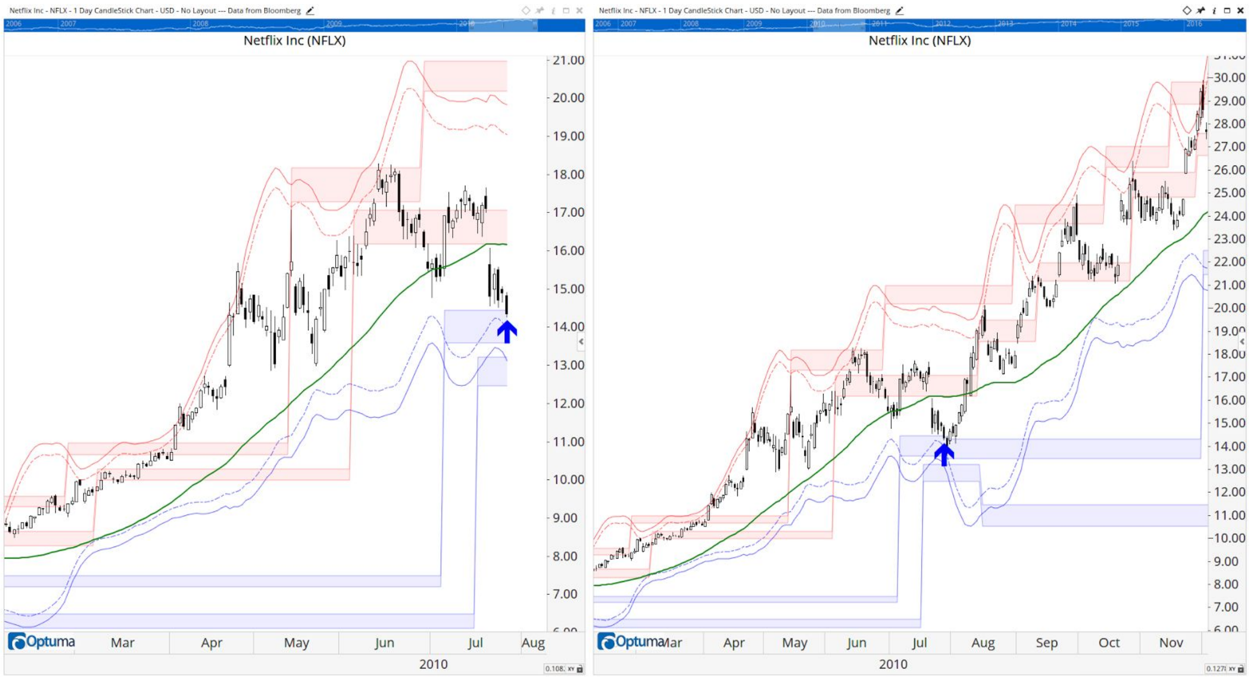


Figure 1.1 and 1.2. Support at VBSR (algorithmically generated) after a 50 day simple fails. The resulting price action anecdotally represents the broad statistical behavior going forward after the VBSR signal.

Risk management is also mandated. Hedging is often merely looked upon as a necessary expense. VBSR can provide additional information that could turn it into an opportunity to mitigate risk and reduce the cost of doing so. Methods which are quantitatively viable today should be timeframe agnostic. They should work equally with data of differing frequencies. VBSR has adaptive elements which accomplish this.

How does VBSR work?

The capabilities above are the product of various proprietary forms of volatility measurement. However the principles they are based on are simple. Immediate volatility extremes are used to project future supply (technical resistance) and demand (technical support) resolution points. What follows is the construct.

At Northington Dahlberg Research the basis starts with a set of volatility bands which have very different properties than others in the public domain. The term for them is N bands.

N bands are designed to identify support and resistance for the ‘right now’ timeframe. If price touches the lower N band, or gets close, it encounters support; thus buyers begin to overpower sellers. The defining advantage is that N bands are designed to contain price.

The concept of VBSR holds that if immediate volatility-base support/resistance can be accurately identified, then so to can future support/resistance.

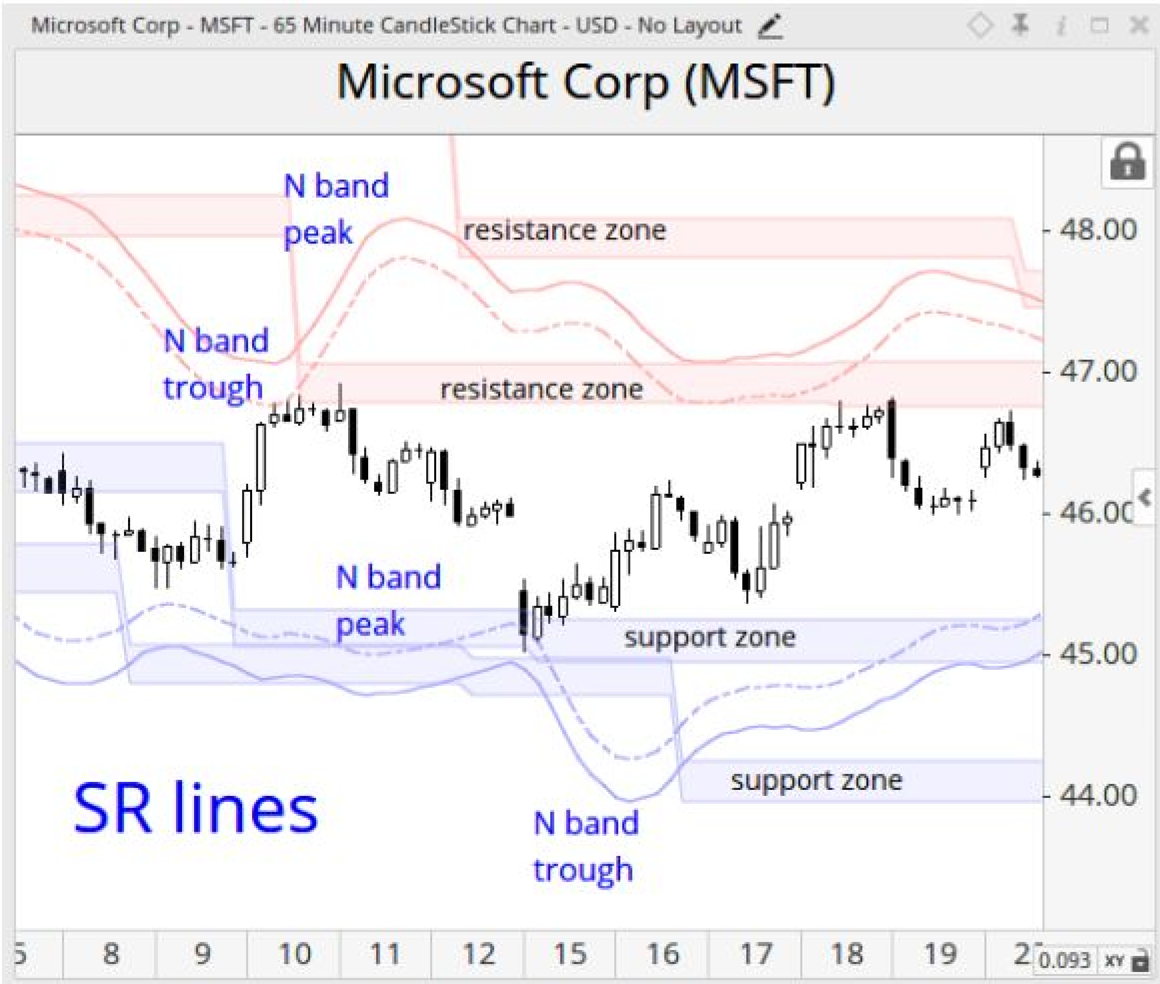


Figure 2 The construct of Volatility-Based Support Resistance (VBSR)

In Figure 2 future zones of resistance or support are identified by peaks and troughs of the N bands. At the top of the chart the upper N band forms a peak. An algorithm identifies this peak and confirms it once variable but significant retracement occurs. This peak level is then projected forward as resistance if price is below it, or support if price is above it. The process is algorithmically generated for the peak of the upper and lower N bands, as well as the troughs of each N band.

Projecting this S/R level forward provides statistically qualified price levels on which to base trading decisions. The forward projected zone is also sometimes referred to as Projected Implied Volatility (PIV).

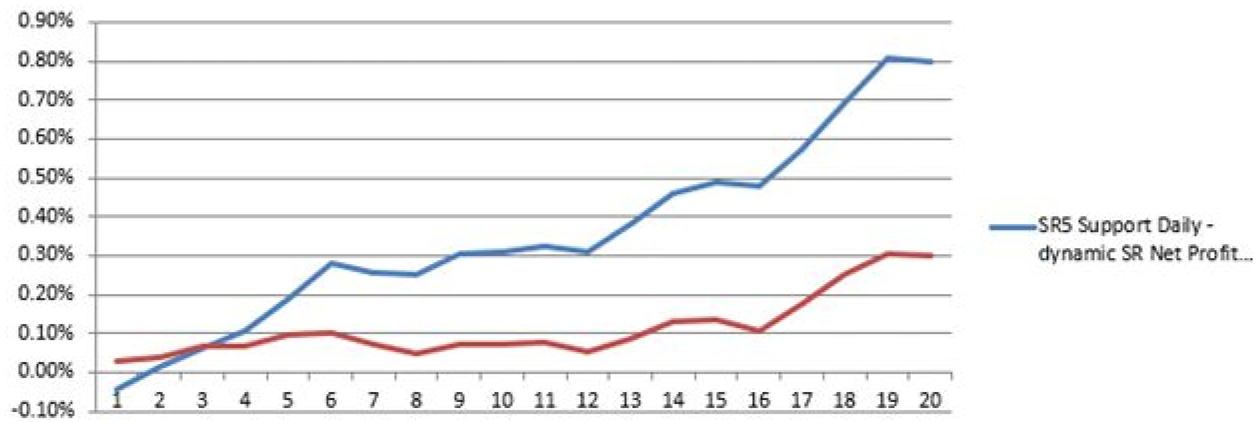


Figure 3 VBSR Test results for support at a lower support zone. See full test data and results in appendix.

Figure 3 illustrates the unmanaged mean forward returns for 20 days following an event where price falls to the support zone formed by the lower N band peak. Full methodology and details of this study are provided in the appendix below.

The upper line is the forward return of the stock price. The lower line shows the movement of the S&P 500 Index. This is accomplished by logging the stock's return, in addition to logging a 1-for-1 concurrent forward return for the index. The study includes a sample of over 10,000, and was conducted in a market neutral time period from 2000 to 2013, where the S&P 500 began and closed at the same level.

Once the stock price falls to support it has a statistical tendency to reverse. Dissimilarly the S&P 500 Index shows a flat average. The differing performances show that VBSR is uncorrelated to the broader market; an important basis for Alpha. It functions without dependence on market timing. Also the de-trended test environment is confirmed by the corresponding flat forward return plot of the Index.

VBSR theory

While this study and others show that VBSR provides quantitative advantages in markets, it doesn't explain why. The specific math and algorithms are trade secrets of Northington Dahlberg Research.

However, we are able to describe the underlying theory of VBSR. Even more importantly we can provide conclusive statistical proof of why VBSR can forecast supply demand decision points.

VBSR theory states as follows:

> N bands are a proxy representation of consolidated levels of implied volatility. N bands are expressed as price levels, not percent, and are designed to approximate the volatility limits of similar derivative contract expirations to that of the chart periodicity; daily, weekly, etc. In that way it is meant to be a 'view' of consolidated implied volatility.
>
> It is the extremes of the N bands which are most significant. The peaks and troughs of the N band levels represent the extremes of concentrations of investor commitment, in the form of contract valuations (due to valuation models and their dependency on the volatility input), reaching points where decisions need to be made and action taken.
>
> Concentrations of commitment at key price levels are what support and resistance is made of. This is because it's at those levels where buy and sell decisions must be made.

Thus projecting forward price levels which were the basis for previous contract commitments identify opportunities for a higher quantity of buyers and sellers to resolve value. The previous price extremes factor heavily into such basis as contract strike price levels, profit/loss targets, and volatility measurements.

Why does VBSR work; the practical basis?

To answer this question, we have to reference an important aspect of any good technical market measure; the market microstructure.

> The Market Microstructure consists of all the components within that market that contribute to price discovery and value delivery. Current academic views are that these components are transaction costs, prices, quotes, volume, liquidity and trading behavior.

Consumer product manufacturers study their target customers' buying influences and preferences. Industrial manufacturers measure macroeconomic factors to forecast demand. These providers do this because there's a direct causal relationship to the forecasting accuracy of their customers' buying behavior.

As technical analysts so to should we base our analysis on causal components of our market microstructures. Earlier mention was made to the role of implied volatility and derivatives as a part of the global financial system's ability to manage risk and regulatory capital requirements.

The current implied volatility of a stock's option contract is an important causal input to price forecasting. It's a relevant, arguably the most relevant, component of a stock's market microstructure. That is to say, large institutions which exert great buying and selling pressures on security prices use implied volatility as a primary input to their mandated risk models and behavior.

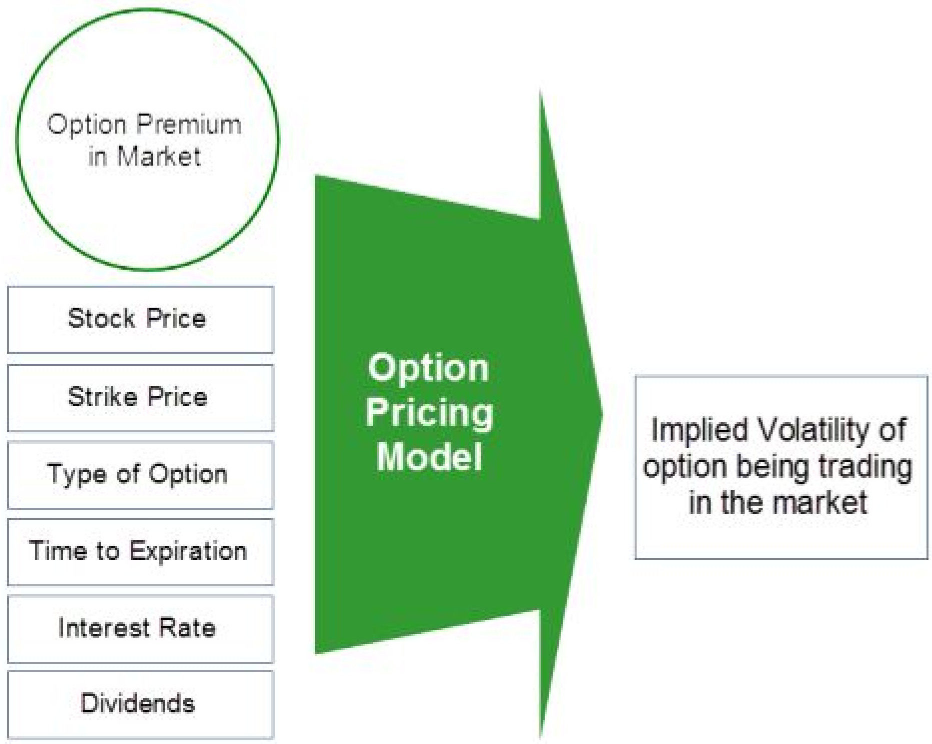


Figure 4 Implied Volatility - the volatility derived from the options traded market price, using an option pricing model.

Earlier mention was made to the role of implied volatility and derivatives as a part of the global financial system's ability to manage risk and regulatory capital requirements. As implied volatility is the primary mathematical input to these valuation models, we should acknowledge that it is a central component of a security's supply/demand valuation process.

With those points stated VBSR provide statistically viable behavior because:

> **VBSR has a cause and effect relationship with the mean reversion of implied volatility.**

Specifically, when implied volatility is trending higher or lower, and price reaches a VBSR support or resistance zone, then implied volatility will likely cease trending and change directions.

In Figure 5 and Figure 6 an illustrative example of the VBSR and implied volatility trend correlation is presented. Apple, Inc. (AAPL : NASDAQ), is shown using VBSR, within a short-term risk / long-term reward analysis framework. The decision time is NASDAQ market close on July 8, 2015. Assume no information known past that time.

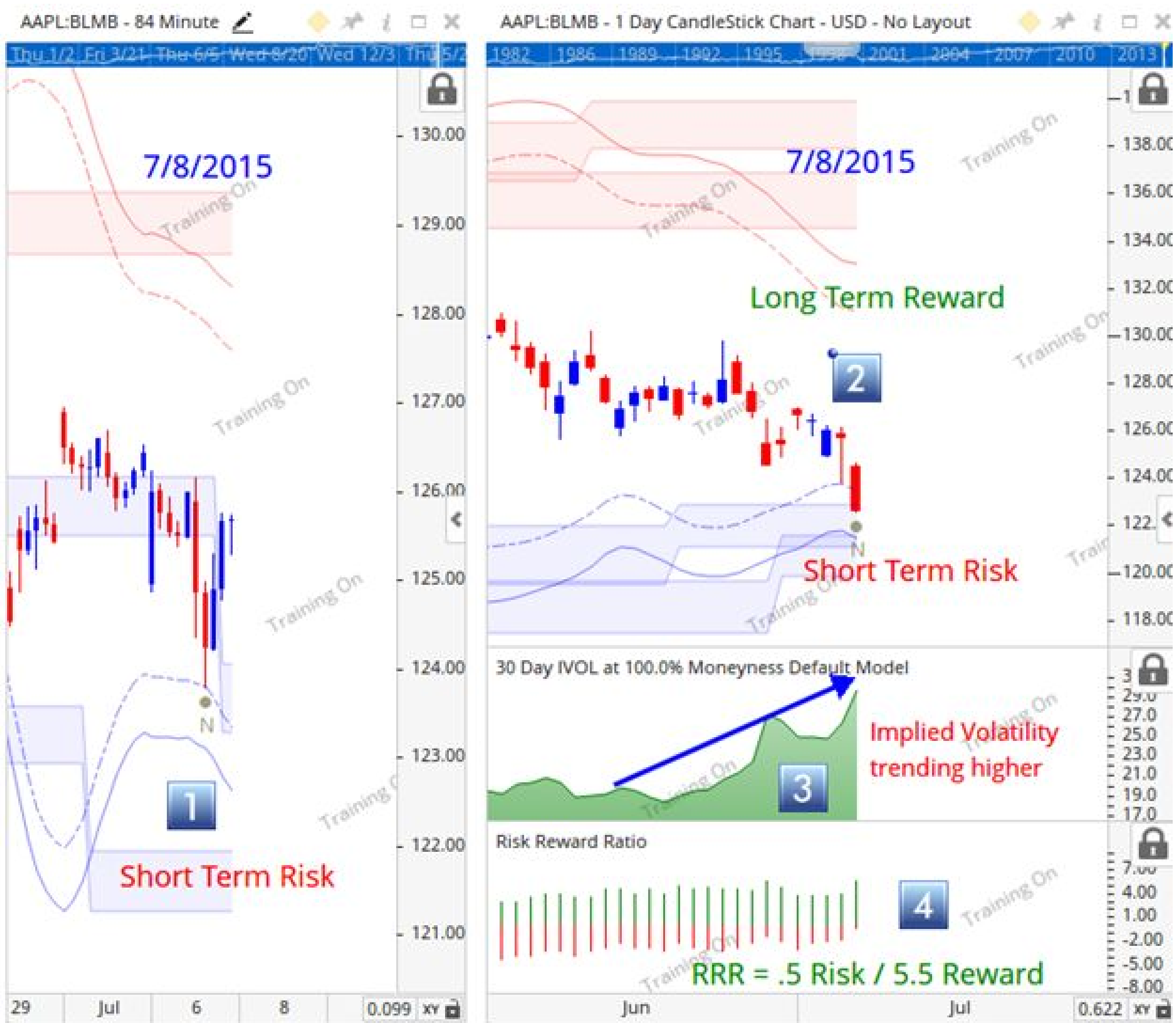


Figure 5 VBSR and directional implied volatility.

Below is the best practice interpretation of the VBSR tools:

The intraday chart shows us that the SR 7/8 support zone is between 121 and 122. This is our short-term risk. Going forward, if price closes below it for 3 bars or more than 3 ATRs, then consider support to be broken. This defines short-term risk.

On the daily chart, price closes inside the lower N band support zone and triggers an N band support signal (N). The current SR 5/6 and 7/8 zones are overlapping, with price closing near the SR 5 line. This all tells us that price is now firmly at support. Based on the performance characteristics of VBSR, the directional movement of price - once it enters this support zone - should change from down to sideways or up over the next 3 to 5 bars. We can also see overhead that the upper N band resistance zone is at approximately 130 to 132. This defines the potential longer-term reward.

Implied volatility has been trending higher. The N band support signal (N) occurring at this point tells us (quantitatively) that 30-day Implied Volatility (IV) should cease trending higher, and likely begin to reverse or move sideways. Thus, if IV reverses then it means market participants believe that price will revert to its mean; short term reversal.

The Risk Reward Ratio (RRR) tool on 7/8/2015 shows a reading of .5 Risk and 5.5 Reward. That’s a good ratio. This tool interprets current support and resistance levels separately, then calculates the quantity of Average True Range units (ATR-40) to those levels.

From a more aggregated point of view, these VBSR technical measurements give weight to a forecast of price trading sideways or reversing higher, for the 3 to 5 trading days going forward. The potential reward is quantified. The potential risk is quantified. These are important pieces of information required for proper trade management.

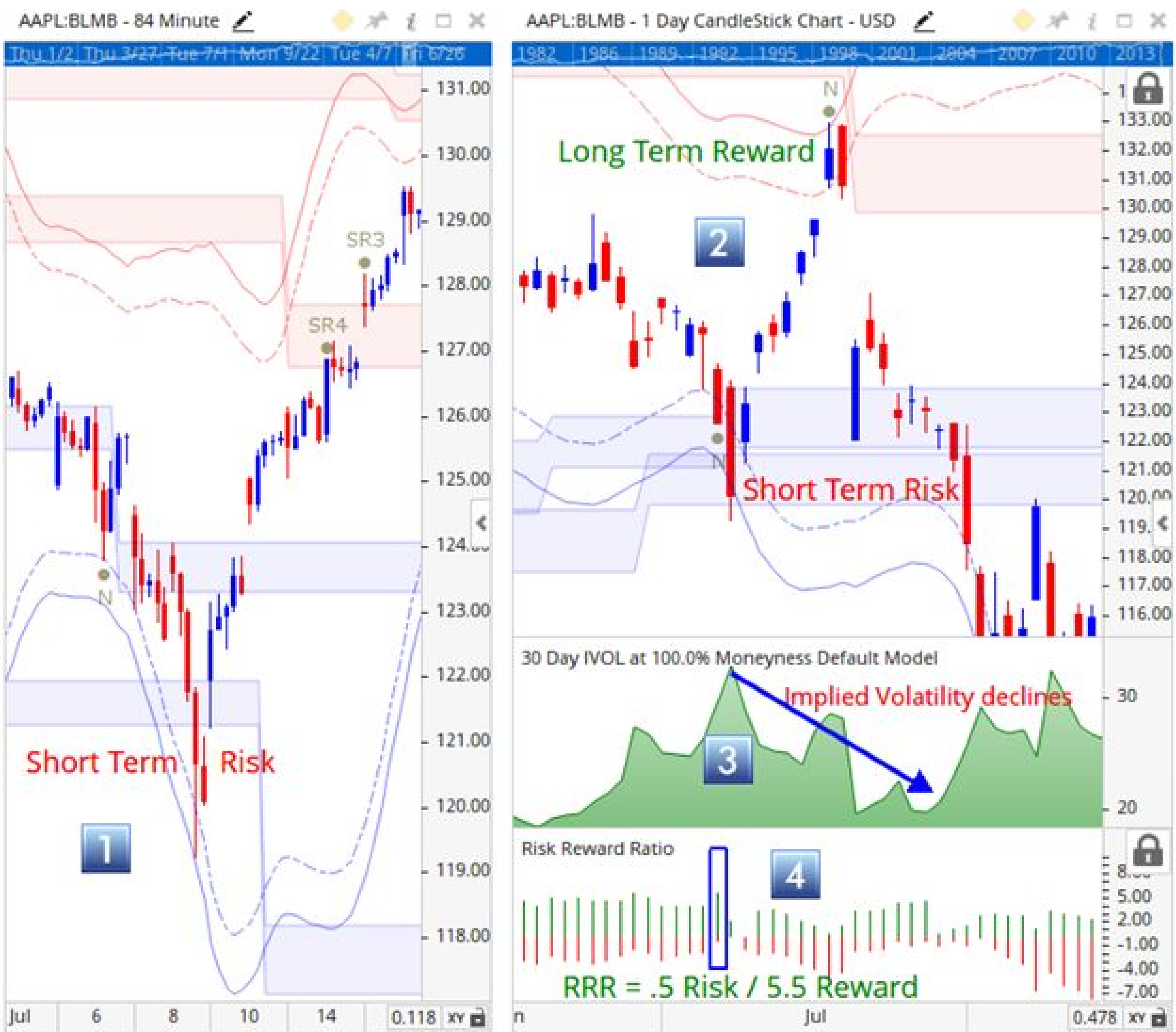


Figure 6 The correlation between VBSR and directional implied volatility.

Shown in Figure 6 above is the resulting price action for July 9th forward. The example is anecdotal. The quantitative study results of this relationship follows.

A study was conducted using the top 10 holdings of the 9 Sector Select ETFs;

Test period from calendar 2004 to 2019

A sample population of 803 instances for the Boolean criteria below:

BEFORE VBSR SUPPORT:
IVOL SLOPE > 0.1 PER DAY
IVOL MEAN SLOPE = 0.36
IVOL MEDIAN SLOPE = 0.27

AFTER VBSR SUPPORT:
IVOL MEAN SLOPE = -0.07
IVOL MEDIAN SLOPE = 10.13
CHANGE = -0.42

PROBABILITY OF NEGATIVE SLOPE = 68%

Figure 7 Summation of the correlation between falling price at VBSR support and rising implied volatility intersecting at a VBSR support zone.

In Figure 7 implied volatility mean reversion is illustrated to show a VBSR support signal (SR5) occurring at the same time point. Price and implied volatility source: Bloomberg, LP.

The directional distribution across the 803 population measured as shown below in Figure 8:

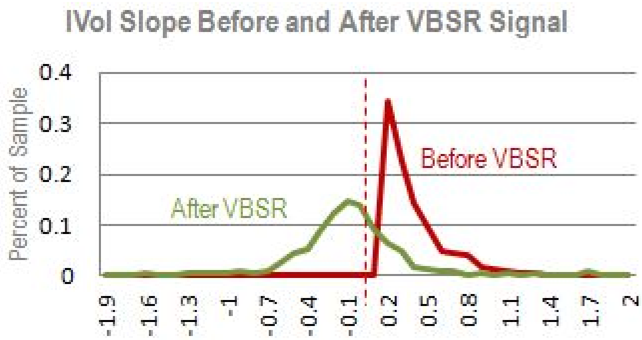


Figure 8 The distribution of implied volatility 20 day linear regression slope before and after a VBSR price support condition.

The distribution of the 20-day slope values; before and after VBSR support occurs. Once VBSR support occurs with rising implied volatility there is a 68% probability that the stock's implied volatility with become net negative.

There are four potential scenarios:

1. *Rising* implied volatility and *falling* stock price (discussed above)
2. *Rising* implied volatility and *rising* stock price
3. *Falling* implied volatility and *falling* stock price
4. *Falling* implied volatility and *rising* stock price

Each of the four conditions were analyzed and produced similar probabilities for implied volatility mean reversion.

Implied Volatility is not just a measurement. It is a tangible part of the market. VBSR correlates to Implied Volatility directionality.

While correlation is not causation, this specific relationship is the underlying event which causes supply and demand to undergo a change resulting in the spot price directional change.

Conclusion

Technical computing capabilities have revolutionized virtually all market participants. So too has it greatly increased the monitoring and regulatory burden of the largest of those that manage massive financial instrument portfolios capable of significantly moving prices. It's commonly echoed with these institutions that their behavior is no longer 'motivated', it's now 'mandated'. Keying in on the available mathematical tools which are in lock-step with these trends is now critical.

Volatility math can be algorithmically derived and used within well-established technical analysis methods. This advantage gives a statistical edge to analysts, portfolio managers and traders. It does so because it effectively measures the more important inputs to commitments, and risk based decision frameworks. Within VBSR resides a methodology proven to work in correlation to directional implied volatility.

This important insight is now available as a key intelligence layer. An investment process which utilizes it as an alpha producing filter can generate additional returns. Just as importantly VBSR can be implemented by quantitative and discretional analysts.

Notes

1. Macroeconomic Assessment Group, established by the Financial Stability Board and the Basel Committee on Banking Supervision; October 10, 2011. Assessment of the macroeconomic impact of higher loss absorbency for global systemically important banks, page 14. (http:/www.fsb.org/wp-content/uploads/r_111010.pdf?page_moved=1)

Table 1

Shares of G-SIBs in domestic financial systems (%)

	Lending to the non-financial private sector			**Total financial system assets**		
	Top 20	**Top 30**	**Top 40**	**Top 20**	**Top 30**	**Top 40**
Minimum	3.50	3.90	7.50	8.20	8.58	13.80
Maximum	50.46	75.21	75.77	68.98	76.64	79.53
Unweighted median	18.93	29.13	39.47	27.77	35.24	46.96
GDP-weighted median	30.39	46.18	48.70	31.48	55.51	66.81
Unweighted mean	23.63	30.85	38.54	30.41	38.02	46.31
GDP-weighted mean	32.11	40.10	43.96	43.02	52.38	57.75

Figures are summary statistics for the share of lending (or assets) in the domestic financial systems of Australia, Brazil, Canada, France, Germany, Italy, Japan, Korea, Mexico, the Netherlands, Spain, Switzerland, the United Kingdom and the United States represented by the first 20/30/40 financial institutions that would be produced by applying the methodology used in Basel Committee (2011a) to end-2009 data. Observation dates for lending and asset shares vary from December 2009 to May 2011. GDP figures are 2010 estimates from the IMF WEO database.

Sources: IMF; national data; BIS calculations.

Appendix

Appendix A
Statistical Back-testing Methodology

Test Population: For back-testing each of the MetaSwing components the individual stocks of the S&P 500 Index are used. The specific makeup is that of the S&P 500 as defined between August 1, 2000 and January 31, 2013.

A graph of the S&P 500 Index, showing the the test period, including two bull and two bear markets over a market neutral time period.

Data Source: All back-testing is performed using daily time series data from Thomson Reuters. The test signals are only those that occur between August 1, 200 and January 31, 2013; approximately 12.5 years.

Market Time Span: The test data was chosen to be market neutral. There is no material difference in the S&P 500 Index from the beginning of the test data time span to the end. This creates a more unbiased, de-trended market environment. Doing so creates test results attained throughout an equal effect of two bull and two bear markets.

Survivorship Bias Filtering:

This phase compensates for testing an Index of stock constituents that does not remain static. There are two means by which survivor bias enters the research universe:

Type 1 Bias: The bias of excluding companies from a research universe that met membership criteria historically but did not on the day the universe was defined. These are poor performers eliminated by delisting or acquisition, prior to current index inclusion.

Type 2 Bias: The bias of including companies in a research universe that did not meet membership criteria until recently. These are outperformers tested for time spans occurring prior to index qualification.

The purpose of ensuring that performance testing is free of survivorship bias, is to directly simulate the trading of index constituents just as one would have done so over time; just as the makeup of the index changed. This significantly improves the probability that future system performance will track historical system performance.

Monte Carlo Simulation: Comprised of a 50,000 iteration, random sampling with replacement. Bootstrapping results are given for ten successively, compounded trades, with an accompanying distribution histogram, and supporting descriptive statistics.

Broad Market Comparison: For each instance of a test signal a concurrent trade using the S&P 500 Index is also measured. The performance of the index is then compared to the test statistic.

Appendix B Study Results for Back-Test of VBSR, SR5 Zone

Performance Statistics -
S/R Lines: *Support*

Test Signal

- The S/R 5 Line price value, when Price (low) descends to =< the S/R 5 Line.
- Price (low) has not been below the S/R 5 Line within the previous 20 periods.
- Any gap down from the previous bar is less than 1% of the close price.

Mean Performance S/R 5 - Support

In the eight day mean performance at right the average potential gain (entry point to high) far exceeds the average potential loss (entry point to low). On the exact same signal days the broader S&P 500 Index experienced no significant under or over performance. Therefore:

- the presence of the test statistic was non-correlated to the broad market.
- it outperformed the broad market.

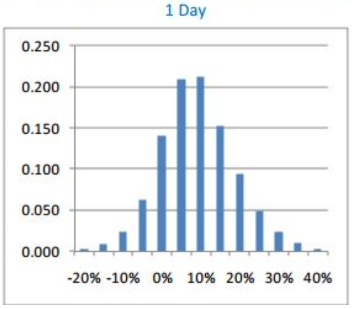
Sample Size = Population 3839	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8
	2.5	2.7	3.3	3.9	4.5	6.6	7.5	7.3
SR 5 Support Profit Potential	2.20%	2.24%	2.32%	2.39%	2.44%	2.53%	2.59%	2.59%
SR 5 Support Loss Potential	-0.88%	-0.83%	-0.70%	-0.62%	-0.54%	-0.38%	-0.35%	-0.36%
S&P 500 Profit Potential	0.78%	0.81%	0.84%	0.82%	0.87%	0.90%	0.92%	0.91%
S&P 500 Loss Potential	-0.72%	-0.72%	-0.71%	-0.67%	-0.65%	-0.60%	-0.58%	-0.61%

Monte Carlo Simulation

Return generated from 10 successive trades (Signal price to Close price): 10,000 iterations

1 Day

Probability of gain	76.1%
Probability of loss	23.9%
Mean return	6.8%
Median return	6.2%
80th percentile return	14%
20th percentile return	-1%
Skewness	0.885
Kurtosis	8.122



3 Day

Probability of gain	71.0%
Probability of loss	29.0%
Mean return	8.6%
Median return	7.3%
80th percentile return	20%
20th percentile return	-3%
Skewness	0.894
Kurtosis	6.312