SPECIAL REPORT

Towards a Macroeconomic Model of Equity Volatility

Maneesh Deshpande
+1 212 526 2953
maneesh.deshpande@barcap.com
BCI, New York

Rohit Bhatia
+1 212 526 0367
rohit.bhatia@barcap.com
BCI, New York

In this reprint of the focus section from our *Volatility Outlook 2010* publication, dated January 11, 2010, we perform a detailed analysis of the macroeconomic and fundamental drivers of equity volatility using data from the past 90 years, with the ultimate goal of forecasting it over medium time scales (about a year).

The final model we construct is based on two sub-models:

• The first sub-model is based on a newly constructed Macroeconomic Risk Indicator (MRI) which is composed of volatilities and levels of several macroeconomic and fundamental variables.

• The second sub-model is a robust predictive model for one-year realized equity volatility based on trailing monthly realized volatilities.

We also include the equity return as an additional explanatory variable.
In our view, a powerful feature of this model is that we can use it to quantify the likely effect of a sustained increase in macroeconomic volatility on equity volatility. We use this model to forecast equity volatility under various scenarios.

TOWARDS A MACROECONOMIC MODEL OF EQUITY VOLATILITY

In this section, using approximately 90 years of data, we perform a detailed analysis of the macroeconomic and fundamental drivers of equity volatility with the ultimate goal of forecasting it over medium time scales (about a year).

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Explanatory variables and methodology

Given the exceptional nature of the current economic situation, we focus on variables that have history stretching back to the early part of the previous century. The key variables we will examine are listed in Figure 1. For calculating equity returns, we splice together returns for the S&P 500 index (available since 1957), S&P 90 Index (available since 1928) and the Dow Jones Industrial Average (available since 1896). These are then used to calculate equity volatility for each calendar month. This forms the basic frequency of our analysis and aligns with the macro data which (except for corporate earnings) is also available on a monthly basis.

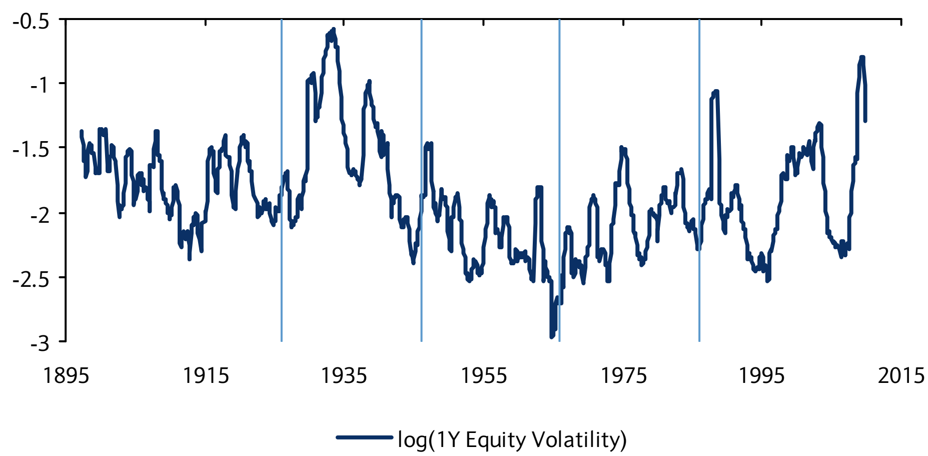
Figure 1: Description of macro variables used

Data Series	Symbol	Availability Since	Frequency	Notes	Source
Industrial Production	IP	1/31/1919	Monthly	Seasonally Adjusted	Federal Reserve / Bloomberg
Consumer Price Index Urban Consumers	CPI	1/31/1913	Monthly	Not Seasonally Adjusted	Bureau of Labor Statistics / Bloomberg
All Commodities Producer Price Index	CPPI	1/31/1913	Monthly	Not Seasonally Adjusted	Bureau of Labor Statistics / Bloomberg
Moody's Bond Indices Corporate AAA	AAA	1/31/1919	Monthly	Average Bond Yield for each month	Moody's Investor Service / Bloomberg
Moody's Bond Indices Corporate BAA	BAA	1/31/1919	Monthly	Average Bond Yield for each month	Moody's Investor Service / Bloomberg
Credit Spread	CS	1/31/1919	Monthly	Calculated as BAA - AAA	Barclays Capital
SPX Corporate Earnings	EARN	1/1/1926	Quarterly interpolated to monthly	Trailing 12M. As reported earnings.	Standard and Poor's / Robert Shiller's website

Source: Barclays Capital

Our goal is to forecast one-year realized equity volatility. However, instead of modelling volatility directly we prefer to model its log value. This has several advantages, as can be seen in Figure 2, which plots the log of one-year equity realized volatility from 1896 to 2009. First, the distribution of log volatilities is much less skewed than it is for volatility. Thus the fitting would be less susceptible to outliers (e.g., the spike due to the crash of 1987 appears much more benign and does not need special handling). Second, the error bars in our model will be based on percentage changes in volatility (rather than differences). Thus, large values of volatility will automatically lead to larger error bars, which is a more desirable and reasonable feature, in our view. Finally, we are automatically assured that volatility can never become negative.

Figure 2: Equity volatility: A long-term perspective



Source: Barclays Capital, Bloomberg

In log space it is also easier to see that equity volatility has undergone multi-decade secular shifts over this time span. We can identify five distinct regimes: the relatively high volatility period prior to the Great Depression, the exceptionally high volatility period during the Great Depression, the steady decline until the 1960s, the subsequent rise after that until the mid-1980s and then a final period marked by extreme lows and highs. Ideally, our model should be able to explain these long-term secular shifts in terms of other more fundamental variables.

A priori, we expect that equity volatility should depend on both the *volatility* and *changes* of the macroeconomic and fundamental variables listed above. We thus calculate both the rolling 12-month standard deviation of monthly returns and their year-over-year changes and examine them as potential explanatory variables. In addition, we will also examine the rolling 12-month average of the *levels* of interest rates, credit spreads and earnings yield. Finally, for obvious reasons, we also include the year-over-year equity return and past realized equity volatilities. Similar to equity volatility we will use the log transforms of all volatilities and levels.

Our data-set spans from January 1926 to November 2009, dictated by the availability of all the explanatory variables. A natural concern with using data over such a long history is the risk of regime shifts. To guard against this possibility, we stress test all our models by analyzing them across four 20-year sub-periods roughly corresponding to the four regimes highlighted above with breakpoints at 1926, 1946, 1986, and 2009. Since we will be doing regressions using overlapping data we are careful to adjust the t-statistics for correlation in errors.

Constructing a Macroeconomic Risk Indicator for Equity volatility

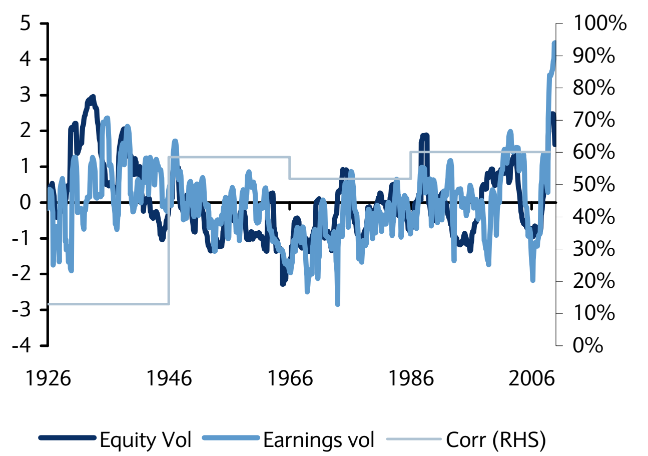
We will first construct a model where we will model the yearly equity volatility versus the above explanatory variables measured over the same time period (contemporaneous model). We begin with examining the dependence of equity volatility on the contemporaneous volatilities and levels which can also be thought of as "risk" variables.

Risk variables

Figure 3 - Figure 10 plot the (logs of) rolling yearly volatilities for our variables. Since the volatilities for different variables have quite different scales we plot the z-score ((value – mean)/standard deviation)) to facilitate comparison. We also show the correlation of each data series with equity volatility over each of our sub-periods. Several interesting features stand out from these graphs:

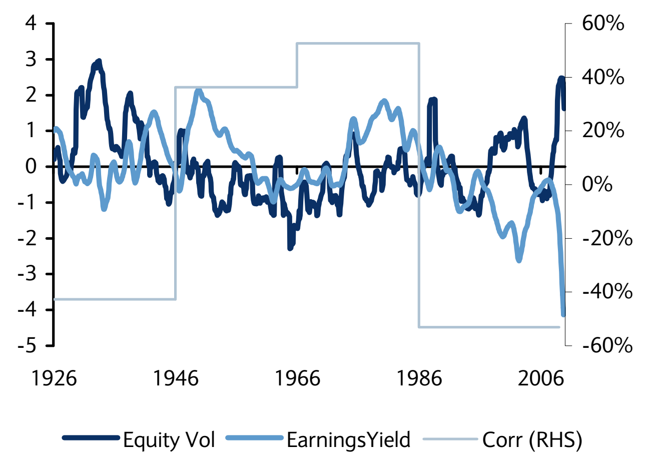
- We see that volatilities of most variables do a reasonable job of tracking equity volatility over this long time span.
- While the correlations vary over different sub-periods, the change is not consistent across different indicators, indicating that a joint regression using multiple variables would be quite beneficial.
- We find that Commodity PPI and Credit Spreads score the best in terms of overall magnitude of correlation and its consistency across time buckets. The correlations versus the other volatilities, while still quite good, show substantial variation.
- The correlation with Equity Yield is quite unstable and has flipped sign over time. It was positive during the Great Depression and more recently, but was consistently negative in the middle two buckets. We reluctantly drop Earnings Yield from further analysis.

Figure 3: Equity vs Earnings volatility



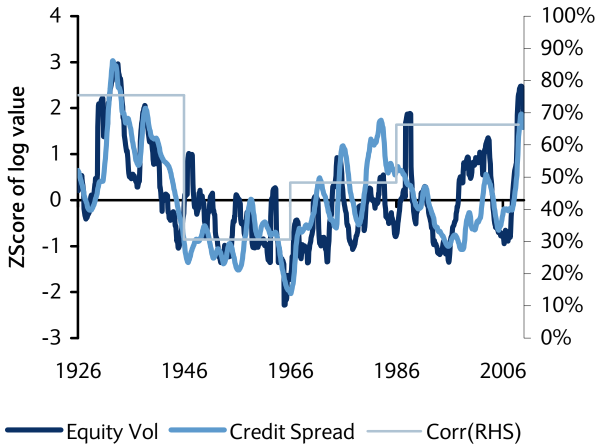
Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M volatilities

Figure 4: Equity volatility vs Earnings yield



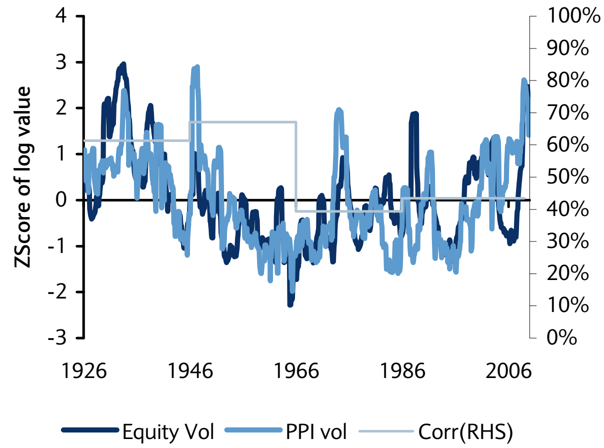
Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M average

Figure 5: Equity volatility vs Credit Spreads



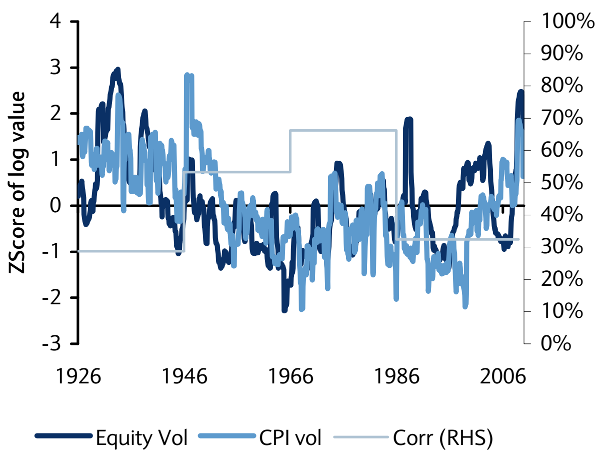
Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M average

Figure 6: Equity vs Commodity PPI volatility



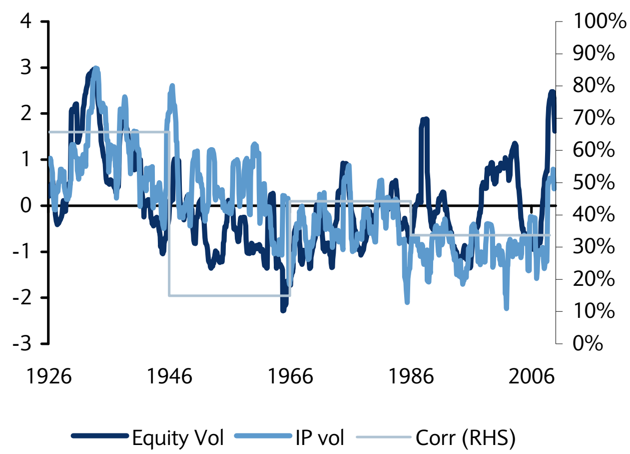
Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M volatilities

Figure 7: Equity vs CPI volatility



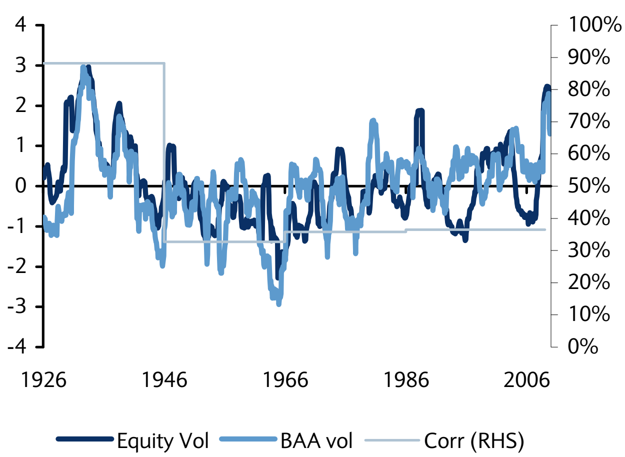
Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M volatilities

Figure 8: Equity vs IP volatility



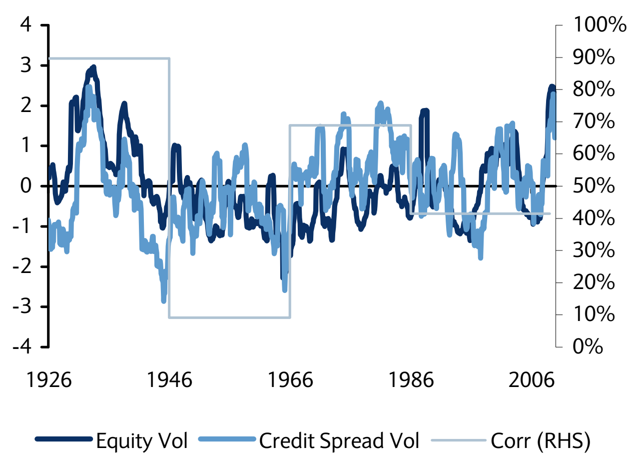
Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M volatilities

Figure 9: Equity vs BAA volatility



Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M volatilities

Figure 10: Equity vs Credit spread volatility



Source: Barclays Capital, Bloomberg. Y axis: ZScore of log of 12M volatilities

We next do a joint linear regression of equity volatility versus our seven variables and find an overall R-square of 69% (or a correlation of 83%). However, we find that some of the betas have perverse (negative) signs and they are also highly unstable across our sub-periods. This is presumably a consequence of the high correlation (~50%) between our explanatory variables, and one way to mitigate this problem is to use principal components analysis (PCA). A multiple regression using the calculated principal components obviously results in the same total R-square since the principal components are simply some linear combinations of the original variables. However, we find that the first principal component has the highest t-statistic and its beta is quite stable across the sub-periods. Figure 11 shows the weights (factor loadings) across different variables and Figure 12 shows the results of doing a regression across the different sub-periods. The overall R-square drops to 64% which, in our opinion, is a small price to pay for stability.

Figure 11: Macro Risk Indicator relative weights

Variable	Weights
Credit Spread Level	43%
Commodity PPI Volatility	41%
CPI Volatility	41%
BAA Volatility	40%
IP Volatility	36%
Earnings Volatility	35%
Credit Spread Volatilty	26%

Source: Barclays Capital

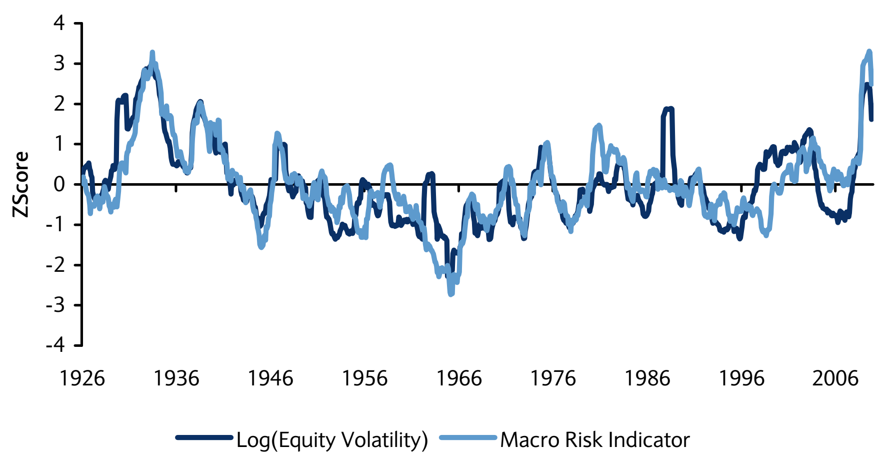
Figure 12: Regression of equity volatility versus Macro Risk Indicator

Start Year	End Year	Intercept	Macro Risk Indicator Beta	R-square
1926	2009	-1.92	0.36	64%
1926	1946	-1.92	0.41	74%
1946	1966	-2.09	0.23	38%
1966	1986	-1.99	0.35	68%
1986	2009	-1.83	0.30	37%

Source: Barclays Capital

This first principal component, which we shall label as the **Macro Risk Indicator**, is thus our best proxy for equity volatility risk based on our fundamental and macro variables. Figure 13 plots it versus equity volatility and we believe it does a very good job in tracking it.

Figure 13: Equity volatility versus Macro Volatility Indicator



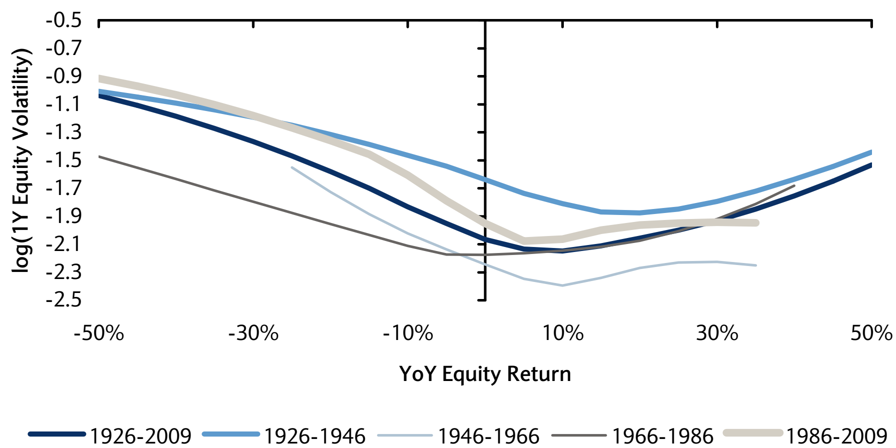
Source: Barclays Capital, Bloomberg

Year-over-year return variables

We next examine the dependence on the trailing 12-month returns of our macro variables which, as discussed above, we also expect to contain additional explanatory power.

Figure 14 shows a locally smoothed fit of 1Y equity volatility on year-over-year equity returns during the same year. While, as expected, we find that negative equity returns are usually associated with elevated equity volatility, this dependence is not monotonic and is distinctly "V-shaped" with larger positive returns also leading to increasing volatility. Thus contrary to popular opinion, rallies are not necessarily low-volatility, grinding affairs. Figure 14 also shows that while the non-linearity is qualitatively present across time, quantitatively it varies substantially, which makes estimating it in a robust manner somewhat tricky.

Figure 14: Non-linear dependence of equity volatility on equity returns



Source: Barclays Capital, Bloomberg

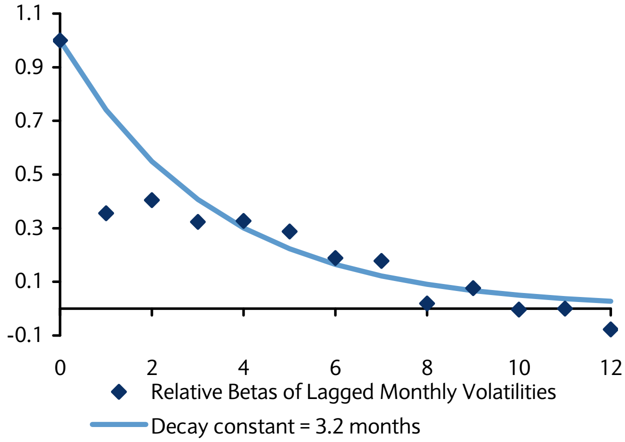
In general, we find that almost all of our explanatory variables have this non-linear dependence. However, the shapes of these curves vary quite dramatically over our sub-periods primarily because each period does not contain enough representative points for both positive and negative changes. Thus, for example, CPI year-over-year changes have not been negative since 1946, which would indicate that equity volatility is positively correlated with inflation. However, the experience during the Great Depression clearly demonstrates the intuitive result that a deflationary environment will increase volatility. Finally, examining the dependence of the residuals of the regression against the Macro Volatility Indicator against the year-over-year return variables shows that they do not add significant explanatory power.

For these reasons, we will be conservative and only include equity return as an additional explanatory variable.

Lagged realized volatilities

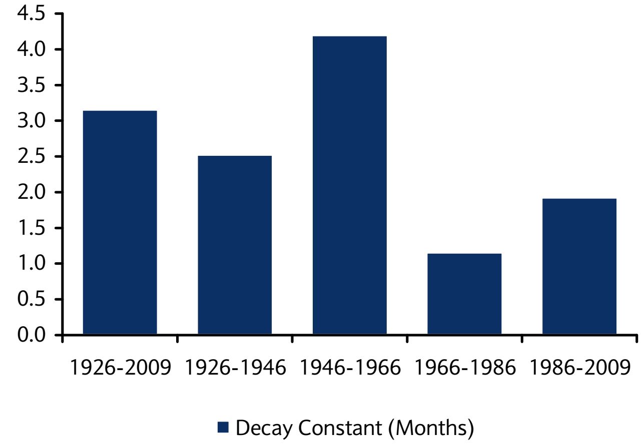
Finally, we turn to the more traditional approach of using lagged realized volatilities. A simple approach would to be to use the lagged one-year equity volatility, but we can do better than that since, intuitively, the effect on past realized volatility should decrease with the lag. A regression of one-year realized volatility against the lagged monthly volatilities indicates that up to at least six months of data is significant with weights rapidly decreasing with increasing lag. Since directly using a set of trailing volatilities is likely to lead to over-fitting, we choose to use an exponential weighting. A non-linear regression fit of the decay constant results in a value of around 3.3 months for the entire sample and is reasonably consistent across the sub-periods (Figure 16).

Figure 15: Dependence of yearly volatility on lagged one-month volatilities decays exponentially



Source: Barclays Capital

Figure 16: Decay constant reasonably stable over time



Source: Barclays Capital

Full model

To summarize, our full model consists of the following variables:

- The Macro Risk factor, which is essentially a weighted combination the z-scored values of the log of credit spread levels and the logs of Commodity PPI, CPI, IP, BAA yields, Credit spreads and Earnings volatilities
- The year-over-year equity return
- The exponentially weighted sum of the lagged log monthly volatilities using a three-month decay constant

Figure 17 shows the betas of our full model. We also show the t-statistics for each coefficient adjusted for the correlation in the residuals induced due to the fact that we are using overlapping returns. Clearly, all the betas are highly significant.

Figure 17: Full model betas

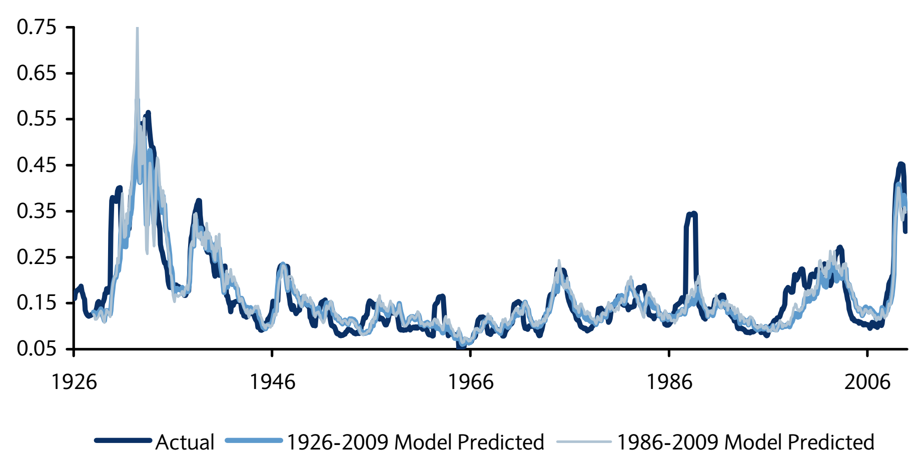
Time Range	Intercept	Macro Vol Indicator	Exp Lagged Volatiltiy	Equity Return	R-square
1926-2009	**-1.04**	**0.20**	**0.42**	**-0.45**	**74%**
1926-1946	-1.48	0.30	0.20	-0.35	79%
1946-1966	-1.46	0.11	0.29	-0.40	44%
1966-1986	-1.74	0.33	0.11	-0.33	74%
1986-2009	-0.73	0.12	0.56	-0.66	72%
Overlapping return adjusted t-statistics					
1926-2009	-4.10	3.20	3.79	-3.20	

Source: Barclays Capital

Finally, Figure 18 shows the predicted volatility using the model over the full time period. To check for robustness, we also plot the predicted values using the model fitted over the last 20 years (1986-2009). Thus, the corresponding points in the graph below pre-1986 are completely out of sample. In our view, the fact that the actual predictions (despite the fluctuation in coefficients) are almost identical attests to the robustness of our methodology.

The final R-square of the model is approximately 74% and the corresponding relative standard error is 23%, which for a 20% volatility corresponds to about 4%. Clearly, we are able to capture much of the overall secular trends and several of the peaks. The main peaks that are not captured are those corresponding to the 1987 crash and the increase in volatility in the middle of 1962. The model is also late in catching the rise in equity volatility during the late 1990s.

Figure 18: Full model results



Source: Barclays Capital, Bloomberg

Volatility forecast

As discussed above, a remarkable feature of the past several decades has been the steady decline in the volatility of macroeconomic indicators. This "Great Moderation" has spawned much literature where the key debate is whether this decline is a result of chance (i.e., the economy has not been subject to large shocks) or a structural change driven by a combination of structural changes in the economy (e.g., a shift to a more service based economy and better inventory management techniques) and effective and more transparent monetary policy. Some proponents of the second hypothesis have even made the bold conjecture that all future recessions would be relatively mild affairs. In our view, the current recession, to put it mildly, is a severe test of the "Great Moderation" hypothesis.

The principal advantage of our model is that it allows us to quantify the effect of a sustained increase in macroeconomic volatility. According to the betas in Figure 17, a 1 standard deviation change in the Macro Risk Indicator would roughly translate to a 20% change in equity volatility, which for a roughly 20% volatility corresponds to a change of 4 volatility points. Looking at Figure 13, while it is unlikely that our Macro Risk Indicator will remain at its current value of around 2 (i.e., 2 standard deviations from its historical mean), it seems reasonable to assume that it will be floored at around 1.

Our base case scenario for SPX return over 2010 is that of a mild rally, in agreement with Barclays Capital's U.S. Equity Strategists. However, we do not rule out a mild pullback under a "W" scenario.

Figure 19 shows the projected volatility based on various scenarios, with our base case scenario in bold. We also show the forecast based on the purely predictive model using lagged one-month realized equity volatilities.

Figure 19: 2010 Equity volatility forecasts

Macro Risk Indicator	SPX Return	Equity 1Y Volatility Forecast
0	20%	16.3%
1	20%	19.6%
1	**10%**	**20.4%**
1	0%	21.3%
1	-10%	22.2%
2	-10%	26.7%
2	-20%	27.8%
Based on lagged 1M equity volatilities:		19.9%

Source: Barclays Capital

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