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Do misalignments predict aggregated stock-market volatility?

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Abstract

This paper considers forecasting regressions of "realized volatility" on a misalignment measure. Results show that this misalignment measure is useful to predict in and out-of-sample stock-market volatility at monthly horizons. The analysis also suggests a threshold effect.

Keywords: Realized volatility; Volatility forecasting; Asymmetry

JEL classification: G12; C53

1. Introduction

This paper aims to address an important but still unanswered question: What is the impact of misalignments on stock-market volatility? In a precedent work (Boucher, 2006), we estimated the common long-term trend in the US earning–price ratio and inflation.[1] We found that the *linear* transitory deviations from this common trend – what we call "misalignments" – exhibit substantial out-of-sample forecasting abilities for stock returns at short and intermediate horizons. In this paper, we consider forecasting regressions of "realized volatility" on this misalignment measure.

Misalignments are likely to affect future volatility for two reasons. First, a large literature documents that market returns exhibit "asymmetric volatility", i.e., positive returns have a smaller impact on future volatility than negative returns of the same absolute magnitude. While the existence of negative asymmetries in market returns is generally not disputed, it is less clear what underlying economic mechanism these asymmetries reflect. Perhaps the most venerable theory is based on leverage effects (Black, 1976; Christie, 1982), whereby a drop in prices raises operating and financial leverage, and hence the volatility of subsequent returns.[2] Thus, any variable which has a predictive ability on stock returns – such as our misalignment measure – potentially has a predictive ability for future volatility.

A second explanation comes from stochastic bubble models of the sort pioneered by Blanchard and Watson (1982). The impact here is due to the popping of the bubble – a low-probability event that produces large negative returns – after a period of persistent misalignments.

The main contribution of the paper is thus ultimately empirical. We find that misalignments are useful to predict in and out-of-sample stock-market volatility at monthly horizons. The analysis also suggests a threshold effect where only misalignments exceeding a certain level of overvaluation have a positive and significant impact on future volatility.

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[1] The long-run relationship between the earning–price ratio and current inflation reflects either the use of nominal interest rates to discount real cash flows by irrational investors (Modigliani and Cohn, 1979) in the present value model, or a subjective inflation risk premium (see Boucher, 2006).

[2] However, it appears that leverage effects are not of sufficient quantitative importance to explain the data (Bekaert and Wu, 2000). An alternative theory is based on a "volatility feedback" mechanism (e.g., Campbell and Hentschel, 1992).

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2. Volatility measurement, misalignment measures and the data set

This paper considers "realized volatility regressions", in which squared daily returns are used to build a proxy for unobserved volatility that is then subjected to time-series regression analysis. A number of papers, including Schwert (1989) and Lettau and Ludvigson (2005), have explored whether macroeconomic variables predict aggregate volatility within the context of realized volatility regressions.

The daily realized variance of market returns is traditionally measured by the squared daily index returns, where the market return is defined as the natural logarithm of the ratio of consecutive daily closing index levels. Andersen et al. (2003) demonstrate that the concept of realized variance is, according to the theory of quadratic variation and under suitable conditions, an asymptotically unbiased estimator of the integrated variance and often performs better than restrictive and complicated parametric GARCH or stochastic volatility models at capturing that volatility. Thus it is a canonical and natural measure of daily return volatility. Moreover, the use of realized volatility permits us to employ traditional time-series procedures for modeling and forecasting based on predetermined conditioning variables.

Following the approach of French et al. (1987) among many others, we sum the squared daily returns on the Standard and Poor's (S&P) composite index to obtain monthly market volatility:

$$V_t = \sum_{j=1}^{J_t} r_{j,t}^2, \tag{1}$$

where J_t denotes the number of trading days in the t-th period (month or quarter in our empirical application) and $r_{j,t}$ indicates the daily return on the S&P 500 index on the j-th trading day of the t-th month.

The aim of this paper is to provide empirical evidence regarding the impact of misalignments, as measured by the deviations in the common trend of the earning–price ratio and the inflation rate, on aggregated volatility. We denote, $\hat{epi}_t$, the deviation of (log) earning–price ratio from its predicted value based on the cointegrating relationship between the earning–price ratio and price inflation. We use the Dynamic Ordinary Least Squares (DOLS) developed by Stock and Watson (1993) to estimate the coefficients of the cointegration relationship, a method that generates optimal estimates of the cointegrating parameters in a multivariate setting.

The data set consists of monthly observations from 1950M1 to 2006M2. Stock prices and earnings per share correspond to the Standard and Poor's composite index.[3] Log price, p_t, is the natural logarithm of the S&P price level in month t. Log earnings, e_t, are the natural logarithm of earnings per share in month t. The inflation rate, i_t, is the percentage change in the Consumer Price Index (All Urban Consumers) published by the BLS.

Our empirical analysis considers a set of forecasting variables prevalent in the empirical literature on predictability of volatility. These variables include the log earning–price ratio, $e_t - p_t$; the commercial paper to Treasury yield spread, CP_t; the default premium, DEF_t, defined as the difference in yields between Moody's Baa and Aaa rated bonds; and the one year Treasury yield, $TBY1_t$ (e.g., Whitelaw, 1994; Lettau and Ludvigson, 2005).[4]

Table 1
Forecasting stock-market volatility

#	Constant (t-stat)	AR(1) (t-stat)	$\hat{epi}_t$ (t-stat)	$e_t - p_t$ (t-stat)	DEF_t (t-stat)	CP_t (t-stat)	$TBY1_t$ (t-stat)	$\bar{R}^2$
1	**0.004**	**0.538**						0.288
	(5.327)	(6.626)						
2	**0.004**	**0.518**	**−0.001**					0.302
	(5.597)	(6.822)	(−2.733)					
3	0.001	**0.528**		−0.001				0.293
	(0.953)	(6.400)		(−1.809)				
4	**0.002**	**0.469**	**−0.003**		**0.001**		**0.015**	0.327
	(4.572)	(4.041)	(−4.094)		(2.086)		(2.154)	
5◆	0.000	**0.398**	**−0.005**		**0.002**	**0.002**	**0.023**	0.360
	(0.809)	(4.042)	(−4.098)		(2.976)	(2.402)	(2.479)	

Note: The table reports estimates from OLS regressions of stock-market volatility on lagged variables. For each regression, the t-statistics, listed in parentheses, rely on a Newey–West correction. Significant coefficients at the 5% level are highlighted in bold. Regressions use data from 1950M1 to 2006M2, except for regression 5 (denoted with a ◆), which begins in the seventh month of 1974, the largest common sample for which all the data are available.

3. In-sample and out-of-sample linear regression results

Table 1 presents regressions of volatility, V_t, on a variety of predictive variables. The table reports the regression coefficients, heteroskedasticity-and-autocorrelation-consistent t-statistics, and adjusted R^2 statistics. There is substantial autocorrelation in measured volatility, thus we include one lag of volatility in our forecasting equations for V_t. The result of estimating a purely autoregressive specification is reported in row 1; past volatility is a statistically significant predictor of future volatility.

The second rows display the forecasting power of $\hat{epi}_t$. The sign of the significant coefficient in this regression is negative. This result implies that an overvaluation ($\hat{epi}_t<0$) has a significant positive impact on future volatility. The third row of Table 1 uses the earning–price ratio to forecast volatility. The coefficient on this variable, like that on $\hat{epi}_t$, is negative, but it is not statistically significant. The rows four and five add additional regressors to the set of forecasting variables for volatility. In these multivariate regressions, all variables have marginal predictive power. These results imply that the forecasting power of $\hat{epi}_t$ for future volatility is robust to the inclusion of these additional regressors and reveal that $\hat{epi}_t$

[3] The S&P data are available from Robert Shiller's home page at http://www.econ.yale.edu/~shiller. The complete documentation for the data sources is also provided here. Data are updated from the Standard and Poor's Web site (S&P 500 Earnings and Estimate Report).

[4] Data are obtained from the FRED II database.

Table 2
One-quarter-ahead forecasts of stock-market volatility: non-nested comparisons

#	Model 1 vs. model 2	MSE_1/MSE_2	MDM test	
			Test statistic	*p* value
Panel A: Cointegrating vector reestimated				
1	$e\hat{p}i_t$ vs. DEF_t	0.9988	1.938	0.058
2	$e\hat{p}i_t$ vs. $TB1Y_t$	0.9842	**3.429**	0.000
3	$e\hat{p}i_t$ vs. $CP_t^{\blacklozenge}$	0.9764	**3.582**	0.000
Panel B: Fixed cointegrating vector				
4	$e\hat{p}i_t$ vs. DEF_t	0.9913	**3.637**	0.001
5	$e\hat{p}i_t$ vs. $TB1Y_t$	0.9730	**4.963**	0.000
6	$e\hat{p}i_t$ vs. $CP_t^{\blacklozenge}$	0.9673	**4.855**	0.000

Note: The MDM test, is a modified Diebold and Mariano (1995) test statistic to test for forecast encompassing between two non-nested models and to account for finite-sample biases. The null hypothesis is that model 2 encompasses model 1. We estimate the cointegration parameters recursively in panel A and using the full sample in panel B. Significant coefficients at the 5% level are highlighted in bold. Regressions use data from 1950M1 to 2006M2, except for regressions 3 and 6 (denoted with a $^{\blacklozenge}$), which begin in the seventh month of 1974, the largest common sample for which all the data are available.

contains information about future volatility that is not included in other forecasting variables.[5]

To assess the robustness of our results, we also conduct an out-of-sample forecasting analysis. We use two statistics to compare the out-of-sample performance of the forecasting models: the mean-squared forecasting error (MSE) ratio and the modified Diebold–Mariano (MDM) encompassing test proposed by Harvey et al. (1998). Two cases are considered. First, agents are assumed to know the cointegration parameters of $e\hat{p}i_t$ which are estimated using the full sample. Second, the cointegration parameters are estimated recursively using only information available at the time of forecast.

Results of the out-of-sample one-quarter-ahead forecast comparisons of excess returns are shown in Table 2. We compare alternatively the model 1 in which the lagged value of $e\hat{p}i_t$ is the sole predictive variable with "competitor models" in which each of the "additional regressors" is the sole predictive variable. A constant is included in each of the forecasting equations.

Results indicate that the $e\hat{p}i_t$ forecasting model produces lower MSE than any of the "competitor" model. Moreover, the MDM encompassing test indicates that the model using lagged $e\hat{p}i_t$ contains information that provides superior forecasts to those produced by most of the other models. The findings are statistically significant at better than the 2% level in almost every case, regardless of whether the cointegrating parameters are reestimated.

4. Non-linear regression results

In this section, we investigate the existence of thresholds effects and the possibility of asymmetry in the impact of misalignments on volatility due for example to bubble-crashes phenomena. We estimate threshold predictive regression models of the following form:[6]

$$V_{t+1} = \delta_1 + \delta_2 I_t e\hat{p}i_t + \delta_3(1 - I_t)e\hat{p}i_t + \varepsilon_{t+1} \qquad (2)$$

with

$$I_t = \begin{cases} 1, & \text{if} \quad e\hat{p}i_t \geq \tau \\ 0, & \text{if} \quad e\hat{p}i_t < \tau \end{cases} \qquad (3)$$

where τ is the threshold and ε_t is the error term. The impact of misalignment on volatility is modeled by $\delta_2 e\hat{p}i_t$, if $e\hat{p}i_t$ according to (3) is above the threshold and by the term $\delta_3 e\hat{p}i_t$, if $e\hat{p}i_t$ is below the threshold.

The threshold value and regression slopes can be obtained by least squares estimations through the procedure of minimizing the concentrated sum of square errors, as recommended by Chan (1993) and Hansen (1999).

Table 3 reports estimates of the threshold predictive models for volatility. The first column presents regressions results where the threshold is chosen arbitrarily to be 0 to evaluate the impact of over/undervaluation on volatility. Surprisingly, $e\hat{p}i_t$ coefficients do not appear significant. We reestimate the threshold predictive model where the threshold is consistently estimated with the Chan's grid search method. These results indicate that only the values of $e\hat{p}i_t$ below the threshold have a significant impact on volatility. Our findings are robust to a subsample analysis. Column 3 presents the estimate of the threshold predictive model with endogenous threshold on the period 1950M1–1995M1 since a large part of the low values of $e\hat{p}i_t$ is observed on the last years of the sample. On this subsample, the results are qualitatively the same.

5. Conclusion

This paper considers forecasting regressions of stock-market "realized volatility" on a misalignment measure defined by the temporary deviations from the common trend between the earning–price ratio and current inflation. Results show that this misalignment measure is useful for predicting in and out-of-sample stock-market volatility at monthly horizons. The analysis also suggests a threshold effect where only misalignments exceeding a certain level of overvaluation have a positive and significant impact on future volatility. These last findings are consistent with the "bubble-crash" hypothesis where the popping of bubbles produces large negative returns and a rise in volatility after a period of persistent overvaluation.

Our results are slightly different from the previous literature. Recent empirical research suggests that some of the same variables that forecast expected stock returns also forecast the conditional volatility of stock returns (e.g., Marquering and Verbeek, 2004; Lettau and Ludvigson, 2005). However these

[5] These results are robust to different specifications and measurements of the stock-market volatility (conditional instead of realized volatility, logarithmic transformation to remove most of the skewness and excess kurtosis in the series, autocorrelation-corrected realized volatilities). To save space, we do not report these additional results here which are available upon request.

[6] To save space, we will report only the results of the threshold predictive regression models. Additional non-linear predictive models, in particular based on the absolute size of the misalignments, were estimated but these results – available upon request – were not conclusive.

Table 3
Threshold predictive regressions of volatility

#	1	2	3
δ_1 (t-stat)	**0.0077** (18.323)	**0.0038** (13.332)	**0.0038** (11.456)
AR(1) (t-stat)	**0.5319** (6.955)	**0.4598** (13.680)	**0.4539** (11.768)
δ_2 (t-stat)	0.0001 (0.106)	0.0006 (1.082)	0.0009 (1.471)
δ_3 (t-stat)	−0.0019 (−1.627)	**−0.0044** (−6.769)	**−0.0003** (−2.154)
$\bar{R}^2$	0.289	0.335	0.218
τ	0	−0.3641	−0.2768
Sample	1950M1–2006M2		1950M1–1995M1

Note: The table reports estimates from OLS threshold predictive regressions of stock-market volatility on the "earning–price-inflation ratio" based on models (2) and (3). The threshold parameter, τ, is consistently estimated via Chan's (1993) method. Newey–West corrected t-statistics appear in parentheses below the coefficient estimate. Significant coefficients at the 5% level are highlighted in bold face.

results are exclusively in-sample and reflect a countercyclical Sharpe ratio.

From an asset allocation and risk-management perspective, a promising direction of future research would be to investigate how our misalignment measure affects the investor's portfolio optimization problem and stress-testing analyses.

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