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Uncertainty of macroeconomic forecasters and the prediction of stock market bubbles¶

Helmut Herwartz§ Konstantin A. Kholodilin*

Abstract

We assess the contribution of macroeconomic uncertainty — approximated by the dispersion of the real GDP survey forecasts — to the *ex post* and *ex ante* prediction of the stock price bubbles. For a panel of six OECD economies covering 24 years, two alternative binary chronologies of price bubble periods are determined and subjected to panel logit regressions conditioning on macroeconomic indicators and expectation uncertainty. Measures of macroeconomic uncertainty improve the ex ante signaling of stock price booms and bubbles.

Keywords: Stock market bubbles; out-of-sample forecasting; consensus forecasts; macroeconomic uncertainty; OECD countries.

JEL classification: G01; G17; E27.

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1 Introduction

The ability to timely diagnose and predict strong and persistent deviations between actual and fundamental equity valuation — so-called *bubbles* — is valuable to minimize the enormous economic cost related to crashes of excess speculative prices. Recently, macroeconomic uncertainty has been considered as a major influential factor of (excess) stock valuation. Bansal and Yaron (2004) develop a theoretical model for consumption and dividend growth rates, and conclude that an increase in economic uncertainty leads to falling asset prices, implying that "financial markets dislike economic uncertainty". Bansal et al. (2005) broadly confirm this theoretical result by means of an empirical analysis for Germany, Japan, UK, and the USA.

Departing from the Bansal and Yaron (2004), Segal et al. (2014) distinguish between good and bad uncertainty. Good uncertainty forecasts an increase in the future economic activity and leads to higher asset prices, whereas bad uncertainty predicts a fall in the future economic activity and leads to lower asset prices. The good and bad uncertainties are based on the positive and negative realized semivariances of the growth rates of some macroeconomic variable, respectively.

Here, we suggest a different definition of expectations uncertainty based on the individual predictions of professional forecasters. We define the uncertainty as the variance of the differences between the next and the current year forecasts. In the middle of upswing (downswing) most forecasts are optimists (pessimists) and so the variance is low. However, towards the end of upswing (downswing) the views become more heterogeneous, the variance goes up, which implies a switch in price trend. We also distinguish the positive (negative) uncertainty, being the variance of positive (negative) forecast differences. In the end of upswing (downswing) positive (negative) uncertainty increases implying that soon the prices will fall (increase). Our interest is on testing three hypotheses:

- H_1 : Macroeconomic uncertainty lowers the probability of speculative bubbles.
- H_2 : Optimist uncertainty reduces the probability of the speculative bubbles.
- H_3 : Pessimist uncertainty raises the probability of the speculative bubbles.

Noting the scarcity of empirical evidence on the relation between uncertainty and stock valuation and on forecasting performance analysis, our aim is to examine the role of macroeconomic uncertainty for the prediction of the stock price bubbles. For model specification we build upon earlier work in Herwartz and Kholodilin (2014), and evaluate the marginal contribution of macroeconomic uncertainty to the forecast accuracy of panel logit regressions.

In section 2, we introduce data, sketch the econometric model and performance measures. Section 3 provides in-sample and out-of-sample evidence on predictive accuracy of the most relevant predictors. Section 4 concludes.

2 Data and logit regressions

2.1 Data

The dependent variable is a binary indicator (bubble=1, no bubble=0). A bubble is defined as a positive deviation of the actual stock price from its Hodrick-Prescott (HP) trend exceeding a certain multiple of the standard deviation of the HP cyclical component, denoted ϕ. Two chronologies are considered: a more liberal ($\phi = 1$) indicating boom or bubble events (for ≈16% of all sample observations), and a conservative chronology ($\phi = 1.5$) indicating bubble periods (for ≈7.5% of sample observations). Similar to Herwartz and Kholodilin (2014) we rely on three groups of predictors describing *i*) macroeconomic situation (real GDP growth, current account balance-to-GDP ratio), *ii*) credit market conditions (real money market interest rate, term spread), and *iii*) stock market variables (returns, volatility) (see Table 1 for variable definitions and sources). The considered cross section consists of France, Germany, Italy, Japan, UK, and the USA, and the data cover the period from 1989 Q1 to 2014 Q2. The panel is unbalanced.

For testing H_1 to H_3 realized uncertainties are gathered from monthly survey forecasts. For the period 1989 to 2010 (2010 to 2014) we use surveys of professional forecasters gathered by Consensus Economics (Focus Economics).[1] Each monthly survey contains the forecasts of real GDP growth for the current year, $y^{i,\tau}_{t|t}$, and for the next year, $y^{i,\tau}_{t+1|t}$, where i, t, and τ indicate an individual forecaster, the year, and the month of year t when forecasts are issued, respectively. For each forecaster positive (negative) values of the difference,

$$\Delta y^{i,\tau}_{t+1|t} = y^{i,\tau}_{t+1|t} - y^{i,\tau}_{t|t}, \tag{1}$$

indicate that he expects the real GDP growth to accelerate (decelerate) within the next year[2]. Forecast uncertainty can be approximated as a variance of the individual forecast differences[3]

$$\sigma^2_q = \frac{1}{3N} \sum_{\tau \in q} \sum_{i=1}^{N} \left(\Delta y^{i,\tau}_{t+1|t} \right)^2 . \tag{2}$$

[1] http://www.consensuseconomics.com/, http://www.focus-economics.com/. Noting that the lists of forecasters in each forecast survey are subject to changes and that these lists are overlapping we do not expect that this change affects our estimation results. Moreover, uncertainty measures are highly aggregated statistics processing the survey information.

[2] The forecasters are overly optimistic: only in 9.6% of the cases they forecast negative growth rates for current year and in only 2.5% for the next year. Most of the negative forecasts are for 2009. This precludes the computation of semivariances based on the forecast levels.

[3] This formula can be justified by the fact that, provided that forecasts are unbiased and efficient, $E(\Delta y^{i,\tau}_{t+1|t}) = E(y^{i,\tau}_{t+1|t}) - E(y^{i,\tau}_{t|t}) = E(y^i_{t+1}) - E(y^i_t) = 0$.

Realized measures of *ex ante* good uncertainty are obtained as a sum of squared positive expected growth rates, [4]

$$\sigma^2_{q+} = \frac{1}{3N} \sum_{\tau \in q} \sum_{i=1}^{N} \left(I_+^{i,\tau} \Delta y^{i,\tau}_{t+1|t} \right)^2, \tag{3}$$

where $I_+^{i,\tau}$ is an indicator function

$$I_+^{i,\tau} = \begin{cases} 1, & \text{if} \quad \Delta y^{i,\tau}_{t+1|t} > 0 \\ 0, & \quad \text{otherwise.} \end{cases} \tag{4}$$

The measure of negative uncertainty, σ^2_{q-}, is computed analogously, and $\sigma^2_q = \sigma^2_{q+} + \sigma^2_{q-}$.

Testing the explanatory and predictive content of macroeconomic uncertainty for the emergence of excess stock valuation amounts to unravel the performance of logit regressions augmented with either σ^2_q or σ^2_{q+} and σ^2_{q-}.

2.2 Panel logit approach

Conditional on presample values logit regressions read as

$$Pr(R_{it} = 1 | x_{it-p}) = F(x_{it-p}\boldsymbol{\beta} + \varepsilon_{it}), i = 1, 2, \ldots, 6, \; t = 1, 2, \ldots, T_i, \tag{5}$$

where $Pr(\bullet)$ is the conditional probability of a speculative bubble to prevail in market i and time t; R_{it} is the chronology of equity valuation, designed to predict the boom/bubble ($\phi = 1$) and purely bubble ($\phi = 1.5$) periods; x_{it} is a vector of explanatory variables; and $\boldsymbol{\beta}$ a parameter vector. $F(\bullet)$ is logistic distribution function and ε_{it} is a disturbance. T_i represents the number of observations available for market i. Throughout, we implement logit models for pooled panel

[4] Segal et al. (2014) regress the realized semivariances upon a set of lagged explanatory variables and compute their predicted values.

data. Prior to pooling we account for fixed effects by subtracting within-group means from all right-hand-side variables, except for the constant. Distinguishing the modeling and prediction of bubbles the lag parameter is set to $p = 0, 2, 4$.

2.3 Measures of forecasting performance

For in-sample modeling we use the common pseudo R^2 statistic (McFadden, 1973) and quadratic probability scores (QPS) (Brie, 1950). The evaluation of out-of-sample performance relies only on the latter statistic. The (square root) QPS is

$$QPS^{\bullet} = \sqrt{\frac{1}{\sum_i T_i} \sum_{i=1}^{N} \sum_{t=1}^{T} (R_{it} - F(x^{\bullet}_{i,t-p} \hat{\boldsymbol{\beta}}^{\bullet}))^2}, \quad (6)$$

where $F(x^{\bullet}_{i,t-p} \hat{\boldsymbol{\beta}}^{\bullet})$ is the model-derived probability of a speculative bubble to appear in period t and market i, '$\bullet$' refers to any specific choice of the right-hand-side regression design. QPS varies between 0 and 1. The lower the QPS, the more precise are predictions of the speculative bubbles. In addition to in-sample modeling we determine out-of-sample cross-sectional "leave-one-out" forecasts by means of sample information available for a particular market i coupled with parameter estimates $\hat{\boldsymbol{\beta}}^{\bullet}$ that exploit data collected over the set of remaining markets. To compare the forecast accuracy of alternative models we use a modified Diebold-Mariano statistic developed by Harvey et al. (1997).

3 Empirical results

We estimate first a general model that includes all relevant predictors. Then, each variable, except for constant, is dropped at a time and the effect of this modification on forecast accuracy is considered. Tables 2 and 3 document estimation results for the conditional analysis of the liberal and conservative chronology, respectively. Negative DM statistics signal that a model with single predictor removed has a worse forecast accuracy than the general model. If, in addition, p-value is smaller than 0.10, the left out variable contributes significantly to the improvement of forecasting performance.

Regarding the estimated impacts of macroeconomic, monetary, and stock market variables the results are generally in line with Herwartz and Kholodilin (2014). Both the variance of the forecasts of the real GDP growth rate and the corresponding positive semivariance are statistically significant and have negative signs. This is in line with H_1 and H_2: growing uncertainty about the macroeconomic prospects reflects deteriorated market expectations and, thus, mutes the probability of stock price bubbles. In case of the optimist semivariance, this implies that previously unanimous optimistic expectations are replaced by more heterogeneous views, since the more clear-sighted experts start suspecting worse times may come soon. Moreover, removing these variables from the model invokes significant forecast deterioration as the QPS and DM-statistics indicate. This result holds for all forecast horizons, $p = 0, 2, 4$ and corroborates both H_1 and H_2. By contrast, the magnitude, significance, and predictive content is much less for pessimist semivariance. However, since the impact of pessimist semivariances on the emergence of excess valuations stays negative, we cannot confirm H_3 directly, but notice that the direction of distinguished effects of semivariances is implied by contrasting H_2 against H_3.

4 Conclusions

We evaluate the ability of macroeconomic uncertainty measures to predict the stock price booms and/or bubbles for France, Germany, Italy, Japan, UK, and the USA over the period 1989:Q1-2014:Q2. As macroeconomic uncertainty measures we used the variance and semivariances of the differences between the next year and this year forecasts of the real GDP growth made by individual professional forecasters.

Panel logit regressions indicate that the forecast uncertainty has statistically significant predictive power. Their predictive ability exceeds that of other macroeconomic and financial variables, which are traditionally used as predictors of excess stock valuation. Thus, we can recommend to include measures of macroeconomic uncertainty in early warning systems.

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Tables

Table 1: Data description

Variable	Abbr.	Definition	Source
Stock price index	STOCK		Datastream
Stock market returns	SRET	$\log(\mathrm{STOCK}_t) - \log(\mathrm{STOCK}_{t-1})$	own calculations
Stock market volatility	SVOL	eq. (2) in Herwartz and Kholodilin (2014)	own calculations
Nominal GDP	GDP	billions of national currency	Datastream
GDP deflator	PGDP	index, 2005=100	IFS
Real GDP	RGDP	GDP / PGDP	own calculations
Current account balance-to-GDP ratio	CAB2GDP		Datastream
Long-term interest rate	LTIR	10-year interest rate	Datastream
Short-term interest rate	MMR	3-month money-market interest rate	Datastream
Real short-term interest rate	RMMR	MMR – Inflation rate	own calculations
term spread	Spread	LTIR – MMR	own calculation
Real GDP growth	RGDP	Forecast for current and next year	Consensus Economics/Focus Economics
Forecast uncertainty	σ_q^2	equation (2)	own calculations
Forecast positive uncertainty	σ_{q+}^2	equation (3)	own calculations

Table 2: Logit results for the liberal chronology ($\phi = 1.0$)

Variable	Coeff.	t-ratio	In-sample R^2	In-sample QPS	Out-of-sample QPS	Modified DM statistic	Modified DM p-value
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				$\phi = 1.0$, $p = 0$			
Constant	-3.468	-9.693	*.222*	*.335*	*.361*		
DGDP	0.147	1.863	.215	.337	.346	2.295	.011
SPREAD	-0.842	-5.810	.144	.346	.368	-1.226	.111
RMMR	-0.197	-3.104	.202	.339	.360	0.417	.339
CAB2GDP	-0.027	-0.464	.221	.335	.358	3.966	.000
SRET	0.057	4.296	.179	.343	.373	-2.863	.002
SVOL	93.49	3.966	.193	.340	.362	-0.302	.381
σ^2_q	-1.038	-5.352	.132	.352	.380	-2.856	.002
$\sigma^2_{q^+}$	-1.215	-5.355	.136	.351	.379	-2.460	.007
$\sigma^2_{q^-}$	-0.620	-2.173	.215	.338	.364	-0.860	.195
				$\phi = 1.0$, $p = 2$			
Constant	-3.052	-9.419	*.159*	*.348*	*.374*		
DGDP	0.142	1.810	.152	.349	.358	1.881	.030
SPREAD	-0.642	-4.934	.107	.356	.379	-0.795	.213
RMMR	-0.198	-3.336	.136	.352	.371	0.467	.320
CAB2GDP	-0.022	-0.408	.159	.348	.372	2.319	.010
SRET	0.057	4.169	.120	.355	.386	-3.314	.000
SVOL	-7.511	-0.284	.159	.348	.372	2.035	.021
σ^2_q	-0.858	-4.711	.089	.361	.389	-2.456	.007
$\sigma^2_{q^+}$	-0.991	-4.799	.089	.361	.391	-2.438	.007
$\sigma^2_{q^-}$	-0.423	-1.409	.159	.348	.372	1.394	.081
				$\phi = 1.0$, $p = 4$			
Constant	-2.716	-9.038	*.137*	*.352*	*.382*		
DGDP	0.151	1.874	.130	.353	.361	2.085	.018
SPREAD	-0.427	-3.473	.112	.357	.383	-0.102	.459
RMMR	-0.179	-3.093	.117	.356	.379	0.614	.269
CAB2GDP	0.004	0.069	.137	.352	.379	1.511	.064
SRET	0.060	4.244	.095	.359	.395	-4.043	.000
SVOL	-67.02	-2.247	.125	.353	.383	-0.233	.407
σ^2_q	-0.633	-3.682	.087	.361	.396	-1.872	.030
$\sigma^2_{q^+}$	-0.710	-3.700	.087	.361	.397	-1.866	.030
$\sigma^2_{q^-}$	-0.340	-1.090	.136	.352	.382	1.226	.109

Logit results for the liberal chronology ($\phi = 1.0$). Columns (2) and (3) document the estimated coefficients and their t-statistics, respectively, for the most general model specification. In-sample pseudo-R^2 and QPS —statistics are in columns (4) and (5), while out-of-sample QPS is in column (6). Columns (7) and (8) report the modified DM statistic and its p-value, respectively. Italic numbers indicate statistics from evaluating the unrestricted model. Further results for R^2, QPS and DM refer to logit designs with single covariates removed. Entries in lines $\sigma^2_{q^+}$ and $\sigma^2_{q^-}$ show marginal effects for models with semivariances for which we do not report marginal impacts of the macroeconomic indicators. For the employed abbreviations see also Table 1.

Table 3: Logit results for the conservative chronology ($\phi = 1.5$)

Variable	Coeff.	t-ratio	In-sample		Out-of-sample	Modified DM	
			R^2	QPS	QPS	statistic	p-value
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\phi = 1.5$, $p = 0$						
Constant	-4.081	-8.545	*.154*	*.252*	*.269*		
DGDP	0.106	1.084	.150	.252	.262	1.869	.031
SPREAD	-0.624	-3.390	.112	.252	.262	2.103	.018
RMMR	-0.145	-1.726	.143	.252	.264	2.641	.004
CAB2GDP	-0.022	-0.292	.153	.252	.266	3.455	.000
SRET	0.048	2.896	.122	.255	.276	-2.485	.007
SVOL	83.92	2.856	.130	.254	.268	0.495	.310
σ_q^2	-0.884	-3.483	.090	.257	.277	-2.279	.012
$\sigma_{q^+}^2$	-1.043	-3.494	.093	.257	.277	-1.505	.067
$\sigma_{q^-}^2$	-0.513	-1.356	.150	.253	.273	-0.805	.211
	$\phi = 1.5$, $p = 2$						
Constant	-3.697	-8.534	*.117*	*.259*	*.286*		
DGDP	0.149	1.485	.110	.260	.267	2.649	.004
SPREAD	-0.302	-1.785	.107	.260	.283	1.058	.145
RMMR	-0.117	-1.469	.110	.260	.280	2.493	.006
CAB2GDP	-0.005	-0.068	.117	.259	.283	1.671	.047
SRET	0.062	3.518	.072	.263	.298	-3.697	.000
SVOL	12.26	0.348	.117	.259	.285	1.797	.036
σ_q^2	-0.756	-3.152	.064	.264	.295	-1.783	.037
$\sigma_{q^+}^2$	-0.858	-3.164	.064	.264	.296	-1.701	.044
$\sigma_{q^-}^2$	-0.406	-0.965	.116	.260	.287	0.503	.307
	$\phi = 1.5$, $p = 4$						
Constant	-3.415	-8.406	*.093*	*.262*	*.296*		
DGDP	0.106	0.985	.090	.262	.273	2.690	.004
SPREAD	-0.203	-1.244	.088	.262	.292	1.530	.062
RMMR	-0.139	-1.776	.083	.262	.287	2.469	.007
CAB2GDP	0.030	0.419	.093	.262	.291	1.518	.064
SRET	0.058	3.144	.056	.264	.303	-1.956	.025
SVOL	-36.09	-0.932	.090	.262	.295	0.472	.318
σ_q^2	-0.545	-2.390	.055	.264	.303	-1.259	.103
$\sigma_{q^+}^2$	-0.625	-2.427	.055	.264	.304	-1.273	.100
$\sigma_{q^-}^2$	-0.266	-0.662	.094	.262	.295	1.808	.035

For further notes see Table 2.