Online Appendix to accompany

A Comprehensive Look at Financial Volatility Prediction by Economic Variables

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A. Methodological Details

In this Appendix, we provide some additional details on the Bayesian methods that are underlying the results discussed in the main text. We first describe the elicitation of prior distributions in the Bayesian Model Averaging (BMA) setup. We then provide some details on the Markov Chain Monte Carlo Model Composition algorithm (MC^3) which is used for sampling from the set of models $\mathcal{M}_1, ..., \mathcal{M}_{2^\kappa}$.

A.1. Prior Elicitation

For ease of exposition, we denote the dependent variable by Y, which is a $T \times 1$ vector of realized volatility as in Eq. (1) of the main paper. The predictive variables are collected in a matrix Z_j which has dimension $T \times k_j$ depending on the particular model $\mathcal{M}_j$. We are considering a linear regression model with i.i.d. errors which are assumed to be normal with mean zero and variance σ^2. It is common in the BMA setup to work with the strict exogeneity assumption of the regressors such that a closed form expression for the likelihood can be derived (see, e.g. Wright, 2008).[1]

We follow most of the extant BMA literature and choose to work with a natural conjugate prior distribution for the model parameters $p(\beta_j|\mathcal{M}_j)$ and $p(\sigma^2)$. Thus, our prior on the predictive coefficients β_j conditional on σ^2 is taken to be a normal distribution

$$\beta_j|\sigma^2 \sim \mathcal{N}(0, \sigma^2\phi(Z_j'Z_j)^{-1}), \tag{A.1}$$

which is centered around zero, i.e. it is expected a-priori that there is no predictive power by the economic variables, and ϕ is a hyperparameter. A higher ϕ means a less informative prior (i.e. a higher prior variance), whereas a lower ϕ (approaching zero) induces more shrinkage towards the non-forecastability case. This prior specification is also known as a so-called g-prior framework and is originally due to Zellner (1986). The prior on the predictive coefficients is proper – an important feature to obtain meaningful Bayes factors for model comparison – but it is relatively uninformative, where the amount of informativeness is controlled by the ϕ hyperparameter. The prior on σ^2 is a standard improper prior, proportional to $1/\sigma^2$.

Given these assumptions, the expression for the marginal likelihood takes the following form

$$p(D|\mathcal{M}_j) \propto (1+\phi)^{-k_j/2} S_j^{-T}, \tag{A.2}$$

where $S_j^2 = Y'Y - Y'Z_j(Z_j'Z_j)^{-1}Z_j'\frac{\phi}{1+\phi}$. The expression in (A.2) is important since it enters Eq. (4) of the main paper and thus plays an essential role for the computation of posterior model probabilities

[1] Of course, in a time-series setup as the one considered here, strict exogeneity is typically violated. Nevertheless, given that this violation is generally considered to be of minor relevance for the forecasting problem, the literature (e.g. Stock and Watson, 2004; Wright, 2008; Faust, Gilchrist, Wright, and Zakrajsek, 2011) generally assumes strict exogeneity, which provides an elegant theoretical framework for model averaging.

$p(\mathcal{M}_j|D)$. Given the likelihood and the prior, the posterior mean of the predictive coefficients takes the form

$$\beta_j|D = \frac{\phi}{1+\phi}(Z_j'Z_j)^{-1}Z_j'Y. \tag{A.3}$$

In this BMA setup there are two modeling choices which require input by the researcher. First, the hyperparameter ϕ must be selected, which controls the degree of informativeness of the prior on the predictive coefficients. We select the ϕ hyperparameter according to the simulation-based recommendations in Fernandez, Ley, and Steel (2001). The second choice is that we assign equal prior probability on the models, i.e. we take $1/2^{\kappa}$ as the prior model probability $p(M_j)$. This implies a prior probability of inclusion for each predictive variable of $\pi = 1/2$ as in Faust, Gilchrist, Wright, and Zakrajsek (2011).

A.2. MC^3 Algorithm

The MC^3 algorithm is a Markov Chain Monte Carlo method of sampling from the distribution of models and has similarities with a Metropolis-Hastings algorithm. For each run r of the algorithm, a candidate model M^* is drawn from the model space $\mathcal{M}_1, ..., \mathcal{M}_{2^\kappa}$ which can either be accepted – if it improves on the model drawn in the previous draw $M^{(r-1)}$ – otherwise it is rejected. If the drawn model is rejected then the chain remains at the previous model $M^{(r-1)}$. The acceptance probability $\Xi(M^{(r-1)}, M^*)$ is expressed as

$$\Xi(M^{(r-1)}, M^*) = \min\left\{\frac{p(D|M^*)p(M^*)}{p(D|M^{(r-1)})p(M^{(r-1)})}; 1\right\}, \tag{A.4}$$

and depends on a comparison of the marginal likelihoods of the drawn model vis-a-vis the previous model of the chain as well as a comparison of the model priors (which are equal in our case). If the number of Monte Carlo draws is large (in our case 500,000) the fraction of draws for the different models converges to the posterior model probability. In order to ensure that the starting value of the chain does not affect the results a burn-in period of 50,000 draws is used.

A.3. Bootstrap Procedure for Out-of-Sample Evaluation

The bootstrap procedure is a model-based wild bootstrap (imposing the null of no predictability by macro-finance variables) and is a variant of the approach considered in Clark and West (2006). The wild bootstrap ensures accurate inference in the presence of conditional heteroskedasticity. In each bootstrap iteration the following steps are performed: (i) A series of i.i.d. standard normal innovations η_t is drawn. (ii) AR(1) models are fitted for both the dependent variables $RV_{i;t}$ as well as each of the κ macro-finance variables in z_t and the residuals ($\hat{\epsilon}_t$, $\hat{\nu}_t$) are saved. (iii) Artificial bootstrap series $RV_{i;t}^{bs}$ and z_t^{bs} are constructed based on the estimated AR(1) parameters and the innovations $\hat{\epsilon}_t\eta_t$, $\hat{\nu}_t\eta_t$. The starting observations of the bootstrap series $RV_{i;0}^{bs}$ and z_0^{bs} are drawn randomly from the actual series.

(iv) The artificial bootstrap data are used to generate recursive forecasts based on models relying on the bootstrapped explanatory macro-finance variables as well as the benchmark AR(1). The corresponding Theil's U statistics $\mathrm{TU}^b s$ are computed. (v) We compute bootstrap p-values as the fraction of times that Theil's U in the bootstrap samples is below the one observed in-sample. Hence, these p-values are one-sided and test the null of equal predictive performance against the alternative of superior performance of the model including macro-finance predictors vis-a-vis the benchmark. The number of bootstrap iterations is set to 1,000.

B. Data Description

Table IA.1. Overview of Predictive Variables

No.	Variable	Abbrev.	Mean	Std.	Skew.	Kurt.	AC(1)
A. Equity Market Variables and Risk Factors							
1	Dividend Price Ratio (Log) (*, †)	D-P	-3.76	0.39	-0.02	1.88	0.99
2	Earnings Price Ratio (Log) (*, †)	E-P	-3.02	0.43	-1.31	6.49	0.98
3	US Market Excess Return (†)	MKT	0.59	4.57	-0.91	5.77	0.10
4	Size Factor (†)	SMB	0.12	3.23	0.81	11.44	-0.03
5	Value Factor (†)	HML	0.35	3.15	0.05	5.54	0.14
6	Short Term Reversal Factor (†)	STR	0.37	3.44	0.17	8.34	-0.02
7	S&P500 Turnover	TURN	0.01	0.16	-0.07	3.38	-0.51
8	Return MSCI World	MSCI	0.73	4.26	-1.20	6.44	0.13
B. Interest Rates, Spreads and Bond Market Factors							
9	T-Bill Rate (Level) (*,†)	T-B	4.56	2.52	-0.02	2.37	1.00
10	Rel. T-Bill Rate (†)	RTB	-0.18	0.86	-0.30	2.85	0.95
11	Long Term Bond Return (*,†)	LTR	0.81	2.97	0.20	4.78	0.02
12	Rel. Bond Rate (†)	RBR	-0.18	0.63	-0.36	4.49	0.87
13	Term Spread (*,†)	T-S	2.33	1.25	-0.25	1.95	0.96
14	Cochrane Piazzesi Factor	C-P	1.22	1.56	0.41	3.34	0.90
C. FX Variables and Risk Factors							
15	Dollar Risk Factor	DOL	0.12	2.19	-0.34	4.02	0.12
16	Carry Trade Factor	C-T	0.05	2.58	-0.69	4.38	0.18
17	Average Forward Discount	AFD	0.18	0.19	0.87	7.83	0.75
D. Liquidity and Credit Risk Variables							
18	Default Spread (*,†)	DEF	0.11	0.43	2.48	12.30	0.94
19	FX Average Bid-ask Spread	BAS	1.43	5.00	1.92	7.46	0.88
20	Pastor-Stambaugh Liquidity Factor	PS	-0.28	6.83	-1.76	10.49	0.00
21	TED Spread	TED	0.07	0.00	1.78	8.67	0.81
E. Macroeconomic Variables							
22	Inflation Rate, Monthly (*,†)	INFM	0.24	0.31	-1.38	11.31	0.47
23	Inflation Rate, YoY	INFA	2.91	1.26	-0.48	4.41	0.95
24	Industrial Production Growth, Monthly	IPM	0.20	0.66	-1.32	10.18	0.23
25	Industrial Production Growth, YoY	IPA	2.24	4.35	-1.60	7.45	0.98
26	Housing Starts	H-S	-2.20	24.90	-0.04	4.52	0.79
27	M1 Growth, Monthly	M1M	0.40	0.79	1.51	13.79	0.18
28	M1 Growth, YoY	M1A	4.81	4.98	0.29	2.31	0.98
29	Orders, Monthly	ORDM	0.11	1.78	0.00	3.15	-0.19
30	Orders, YoY	ORDA	1.20	6.93	-1.51	8.49	0.93
31	Return CRB Spot	CRB	0.25	2.74	-1.76	17.62	0.25
32	Capacity Utilization	CAP	0.02	0.66	-1.07	8.95	0.25
33	Employment Growth	EMPL	0.11	0.19	-0.37	7.40	0.65
34	Consumer Sentiment	SENT	0.01	4.70	0.07	5.66	0.00
35	Consumer Confidence	CONF	0.02	8.25	-0.29	9.94	0.07
36	Diffusion Index	DIFF	8.68	16.91	-0.64	3.57	0.83
37	Chicago PM Business Barometer	PMBB	55.15	7.33	-0.37	3.37	0.88
38	ISM PMI	PMI	52.08	5.35	-0.39	3.77	0.93

Notes: The table shows the summary statistics for the macro-finance predictive variables. The reported statistics include the mean, standard deviation (Std.), Skewness (Skew.), Kurtosis (Kurt.), as well as the first order autocorrelation coefficient (AC(1)). An asterisk (*) denotes that the variable is also part of the Goyal and Welch (2008) dataset, † denotes that the variable is included in set of predictors in case of the long U.S. equity sample from 12/1926-12/2010 ("Long"). The sample period over which the summary statistics for the predictors are computed is from 01/1983-12/2010 ("Short").

Table IA.2. Predictive Variables: Data Sources and Construction

No.	Variable	Abbrev.	Data Source
A. Equity Market Variables and Risk Factors			
1	Dividend Price Ratio (Log) (*, †)	D-P	Dividends over the past year (12-month moving sum) relative to current market prices (in logs); S&P 500 index; Robert Shiller's website.
2	Earnings Price Ratio (Log) (*, †)	E-P	Earnings over the past year (12-month moving sum) relative to current market prices (in logs); S&P 500 index; Robert Shiller's website.
3	US Market Excess Return (†)	MKT	Fama-French's market factor: U.S. stock market return minus one-month T-Bill rate; Kenneth French's website.
4	Size Factor (†)	SMB	Fama-French's SMB factor: Return on small stocks minus return on big stocks; Kenneth French's website.
5	Value Factor (†)	HML	Fama-French's HML factor: Return on value stocks minus return on growth stock; Kenneth French's website.
6	Short Term Reversal Factor (†)	STR	Fama-French's short-term reversal factor: Return on stocks with low prior one-month return minus return on stock with high prior return.
7	S&P500 Turnover	TURN	Turnover for the S&P500; CRSP
8	Return MSCI World	MSCI	Return on the MSCI world stock market index; Datastream
B. Interest rates, Spreads and Bond Market Factors			
9	T-Bill Rate (Level) (*,†)	T-B	Three-month T-Bill rate, Goyal/Welch data and Datastream
10	Rel. T-Bill Rate (†)	RTB	T-Bill rate minus its 12 month moving average; Goyal/Welch data and Datastream
11	Long Term Bond Return (*,†)	LTR	Rate of return on long term government bonds; Goyal/Welch data and Datastream
12	Rel. Bond Rate (†)	RBR	Long-term bond yield minus its 12 month moving average; Goyal/Welch data and Datastream
13	Term Spread (*,†)	T-S	Difference of long-term bond yield and three-month T-Bill rate; Goyal/Welch data and Datastream
14	Cochrane Piazzesi Factor	C-P	Measure of bond risk premia; recursively estimated based on Fama-Bliss data; CRSP.
C. FX variables and Risk Factors			
15	Return on Dollar Risk Factor	DOL	FX risk premium measure; Average premium for bearing FX risk; BBI/Reuters (Datastream), Own Construction
16	Carry Trade Factor	C-T	Return on high interest rate currencies minus return on low interest rate currencies; BBI/Reuters (Datastream), Own Construction
17	Average Forward Discount	AFD	Aggregate predictor of FX returns calculated from forward rates and spot rates; BBI/Reuters FX data, Datastream, Own Construction

Table IA.2. Continued.

D. Liquidity and Credit Risk Variables			
18	Default Spread (*,†)	DEF	Measure of default risk of corporate bonds; difference of BAA and AAA bond yields; Goyal-Welch Data and Datastream.
19	FX Average Bid-ask Spread	BAS	Measure of illiquidity in the foreign exchange market calculated from quoted bid-ask spreads; BBI/Reuters (Datastream), own construction
20	Pastor-Stambaugh Liquidity Factor	PS	Measure of stock market liquidity based on price reversals; CRSP
21	TED Spread	TED	Measure of funding Illiquidity, difference of 3 Month Libor rate minus 3 month T-Bill rate; Datastream
E. Macroeconomic Variables			
22	Inflation Rate, Monthly (*,†)	INFM	Monthly (log) growth rate of the U.S. consumer price index; Datastream
23	Inflation Rate, YoY	INFA	Year-over year (log) growth rate of the U.S. consumer price index; Datastream
24	Industrial Production Growth, Monthly	IPM	Monthly (log) growth rate of U.S. industrial production; Datastream
25	Industrial Production Growth, YoY	IPA	Year-over year (log) growth rate of U.S. industrial production; Datastream
26	Housing Starts	H-S	Monthly change in housing started; Datastream
27	M1 Growth, Monthly	M1M	Monthly (log) growth rate of U.S. M1; Datastream
28	M1 Growth, YoY	M1A	Year-over-year (log) growth rate of U.S. M1; Datastream
29	Orders, Monthly	ORDM	New orders of consumer goods and materials; Year-over year (log) growth rate, Datastream
30	Orders, YoY	ORDA	New orders of consumer goods and materials; Monthly (log) growth rate, Datastream
31	Return CRB Spot	CRB	Measure of growth in commodity prices; annual log difference of CRB spot index; Datastream
32	Capacity Utilization	CAP	Datastream
33	Employment Growth	EMPL	Datastream
34	Consumer Sentiment	SENT	Monthly change in University of Michigan consumer sentiment; Datastream
35	Consumer Confidence	CONF	Monthly change in consumer confidence index; Datastream
36	Diffusion Index	DIFF	Philadelphia Fed Business Outlook Survey Diffusion Index, Datastream
37	Chicago PM Business Barometer	PMBB	Datastream
38	ISM PMI	PMI	Monthly change in purchasing manager index; Datastream

Notes:

(*) Variable is among the predictors considered in Goyal and Welch (2008).

(†) denotes that the variable is included in set of predictors in case of the long-term sample from 12/1926-12/2010.

C. Additional Material

Table IA.3. Summary Statistics: Realized Volatility, Individual FX rates

Panel A.	Mean	Std.	Skew.	Kurt.	JB p-val.	AC(1)	AC(2)	AC(3)
EURUSD	-3.58	0.31	0.07	3.36	0.38	0.53	0.42	0.32
JPYUSD	-3.58	0.34	0.20	3.56	0.04	0.42	0.34	0.26
GBPUSD	-3.67	0.36	0.40	3.25	0.01	0.61	0.56	0.46
CHFUSD	-3.49	0.29	0.15	3.52	0.09	0.45	0.38	0.27

Panel B.	**Correlations**			
	EURUSD	JPYUSD	GBPUSD	CHFUSD
EURUSD	1.00			
JPYUSD	0.39	1.00		
GBPUSD	0.73	0.23	1.00	
CHFUSD	0.88	0.47	0.69	1.00
FX-Aggregate	0.81	0.33	0.82	0.73

Notes: The table shows summary statistics of realized volatility for individual major exchange rates. The realized volatility series are defined as the log of the square root of the realized variance. The reported statistics in Panel A include the mean, standard deviation (Std.), Skewness (Skew.), Kurtosis (Kurt.), the p-value from the Jarque-Bera test for normality (JB p-val.) as well as first (AC(1)), second (AC(2)), and third order (AC(3)) autocorrelation coefficients. Panel B reports the correlations between the different volatility series. The sample period is from 01/1983-12/2010.

Table IA.4. Predictability for Several Asset Classes ("Short"), Higher-order AR terms

	Composite Model			Post.	Post.			*Top 5 Models*				
Panel A. Aggregate-FX	No.	Variable	$\pi \mid y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.376	0.072	5.21		1	1	1	1	1
	2	AFD	**0.98**	0.070	0.025	2.80		1	1	1	1	1
	3	TED	**0.80**	0.046	0.032	1.45		1	1	1	1	1
	4	RV(t-2)	**0.72**	0.116	0.094	1.24		1	1	1	1	1
	5	IPM	**0.68**	-0.041	0.047	-0.88		1	1	1	1	1
	6	INFA	**0.65**	0.036	0.034	1.07		1	1	1	0	0
	7	M1A	**0.63**	0.040	0.038	1.04		1	1	1	1	0
	8	H-S	0.46	-0.020	0.027	-0.75		0	0	1	0	0
	R_a^2	0.552					R^2	0.527	0.542	0.550	0.550	0.533
	R_b^2	0.478					$\bar{R}^2$	0.519	0.532	0.539	0.539	0.524
Panel B. Bonds	*Composite Model* No.	Variable	$\pi \mid y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.393	0.075	5.25		1	1	1	1	1
	2	TURN	**0.88**	-0.043	0.024	-1.76		1	1	1	1	1
	3	RV(t-3)	**0.83**	0.142	0.091	1.57		1	1	1	1	0
	4	DEF	**0.59**	0.033	0.034	0.96		1	1	0	0	1
	5	T-S	0.49	0.025	0.032	0.79		0	0	0	0	1
	6	M1A	0.39	0.019	0.029	0.65		0	1	1	1	0
	7	TED	0.33	0.013	0.023	0.56		0	0	0	1	0
	8	IPM	0.18	-0.006	0.019	-0.30		0	0	0	0	0
	R_a^2	0.443					R^2	0.435	0.425	0.433	0.423	0.433
	R_b^2	0.398					$\bar{R}^2$	0.427	0.418	0.425	0.416	0.424
Panel C. Stocks	*Composite Model* No.	Variable	$\pi \mid y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.344	0.072	4.75		1	1	1	1	1
	2	MKTRF	**0.90**	-0.068	0.031	-2.16		1	1	1	1	1
	3	RV(t-2)	**0.80**	0.155	0.100	1.54		0	1	1	0	1
	4	D-P	**0.75**	-0.065	0.047	-1.36		1	1	1	1	1
	5	TED	**0.74**	0.051	0.038	1.33		1	1	1	1	1
	6	RV(t-3)	**0.72**	0.117	0.092	1.27		1	0	1	1	0
	7	DEF	**0.51**	0.038	0.043	0.87		1	1	1	1	1
	8	STR	0.45	-0.018	0.024	-0.76		0	0	1	1	1
	R_a^2	0.613					R^2	0.604	0.596	0.596	0.610	0.601
	R_b^2	0.547					$\bar{R}^2$	0.595	0.589	0.588	0.600	0.593
Panel D. Commod.	*Composite Model* No.	Variable	$\pi \mid y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.447	0.066	6.81		1	1	1	1	1
	2	RV(t-2)	**0.99**	0.252	0.071	3.54		1	1	1	1	1
	3	H-S	**0.72**	-0.040	0.030	-1.32		1	1	1	1	1
	4	D-P	**0.63**	-0.035	0.032	-1.10		1	1	1	1	1
	5	T-B	0.28	-0.014	0.027	-0.52		0	0	0	0	0
	6	RV(t-3)	0.27	0.031	0.061	0.51		1	0	0	0	0
	7	C-P	0.24	-0.010	0.022	-0.47		0	0	0	0	0
	8	TURN	0.19	-0.005	0.013	-0.39		0	0	0	0	0
	R_a^2	0.674					R^2	0.664	0.669	0.667	0.667	0.667
	R_b^2	0.649					$\bar{R}^2$	0.660	0.664	0.662	0.662	0.662

Notes: This table reports in-sample predictability results for aggregate FX volatility, U.S. bond market volatility, equity market volatility (short-term sample) and commodity market volatility obtained from a Bayesian Model Averaging approach with a MC^3 algorithm. Additional AR terms (RV(t-2) and RV(t-3)) are included as predictors in the model search besides one lag of the dependent variable (RV(t-1)). The results display the results for the best 8 predictors, as ranked according to the posterior probability of inclusion $\pi|y$ (sorted in descending order). Moreover the table reports posterior means, standard deviation and BMA t-ratios of the best predictors (reflecting model uncertainty). Inclusion of the specific variable in the Top 5 models (according to the posterior model probability) is indicated by 1. R_a^2 denotes a pseudo-R^2 based on the composite Bayesian model, R_b^2 shows the R^2 of the benchmark model (AR(1)). R^2 and adjusted R^2 ($\bar{R}^2$) are reported for the best 5 model specifications. The sample period is 01/1983-12/2010.

Table IA.5. Predictability FX Volatility ("Short"): Individual Currencies

Panel A. EUR	*Composite Model* No.	Variable	$\pi\|y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.421	0.057	7.35		1	1	1	1	1
	2	CRB	**0.80**	-0.037	0.024	-1.55		1	1	1	1	1
	3	AFD	**0.78**	0.040	0.027	1.50		1	1	1	1	1
	4	IPM	0.50	-0.023	0.029	-0.80		1	0	1	1	1
	5	H-S	0.40	-0.016	0.024	-0.70		1	1	0	0	0
	6	INFM	0.39	-0.014	0.021	-0.68		0	0	0	1	1
	7	C-P	0.34	0.014	0.023	0.62		1	1	0	0	1
	8	CAP	0.31	-0.011	0.025	-0.43		0	0	0	0	0
	R_a^2	0.323					R^2	0.298	0.295	0.308	0.307	0.307
	R_b^2	0.205					$\bar{R}^2$	0.290	0.287	0.297	0.297	0.296

Panel B. JPY	*Composite Model* No.	Variable	$\pi\|y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	BAS	**0.99**	0.088	0.025	3.51		1	1	1	1	1
	2	RV(t-1)	**0.97**	0.207	0.070	2.96		1	1	1	1	1
	3	DIFF	**0.97**	-0.097	0.038	-2.57		1	1	1	1	1
	4	TED	**0.74**	0.043	0.032	1.36		1	1	1	0	0
	5	TB	**0.60**	-0.050	0.048	-1.05		0	1	0	0	0
	6	C-P	**0.58**	-0.030	0.030	-1.00		1	0	1	1	1
	7	E-P	**0.53**	-0.042	0.046	-0.92		1	0	1	1	1
	8	PMBB	**0.52**	0.042	0.047	0.90		1	0	1	1	1
	R_a^2	0.342					R^2	0.316	0.300	0.311	0.323	0.322
	R_b^2	0.180					$\bar{R}^2$	0.303	0.289	0.298	0.308	0.307

Panel C. GBP	*Composite Model* No.	Variable	$\pi\|y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.401	0.061	6.57		1	1	1	1	1
	2	HS	**0.94**	-0.059	0.024	-2.44		1	1	1	1	1
	3	INFA	**0.85**	0.055	0.031	1.77		1	1	1	1	1
	4	AFD	**0.72**	0.037	0.029	1.30		1	0	1	1	1
	5	M1M	**0.68**	0.035	0.030	1.20		1	1	1	0	1
	6	M1A	**0.66**	0.047	0.040	1.16		1	1	1	1	1
	7	TED	0.37	0.016	0.025	0.65		1	0	0	0	0
	8	IPM	0.31	-0.013	0.026	-0.51		0	0	1	1	0
	R_a^2	0.499					R^2	0.481	0.488	0.468	0.487	0.477
	R_b^2	0.368					$\bar{R}^2$	0.471	0.477	0.459	0.476	0.468

Panel D. CHF	*Composite Model* No.	Variable	$\pi\|y$	Post. Mean	Post. STD	t-ratio		*Top 5 Models* (i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.329	0.061	5.42		1	1	1	1	1
	2	AFD	**0.92**	0.056	0.024	2.30		1	1	1	1	1
	3	CRB	**0.62**	-0.025	0.023	-1.07		1	1	1	1	1
	4	IPM	0.47	-0.021	0.028	-0.77		0	0	1	1	0
	5	CAP	0.43	-0.019	0.027	-0.69		1	1	0	0	1
	6	H-S	0.26	-0.009	0.018	-0.50		0	0	0	0	0
	7	T-S	0.25	0.011	0.022	0.48		0	0	0	0	0
	8	TED	0.24	0.008	0.018	0.45		0	0	0	0	0
	R_a^2	0.323					R^2	0.298	0.295	0.308	0.307	0.307
	R_b^2	0.205					$\bar{R}^2$	0.290	0.287	0.297	0.297	0.296

Notes: This table reports in-sample predictability results for foreign exchange volatility for several major exchange rates vis-a-vis USD based on a Bayesian Model Averaging approach with a MC^3 algorithm. The results are obtained with a set of predictors which contains the lagged dependent variable RV(t-1), results based on a benchmark with higher order AR terms are reported in table IA.6. The table display the results for the best 8 predictors, as ranked according to the posterior probability of inclusion $\pi|y$ (sorted in descending order). Moreover the table reports posterior means, standard deviation and BMA t-ratios of the best predictors (reflecting model uncertainty). Inclusion of the specific variable in the Top 5 models (according to the posterior model probability) is indicated by 1. R_a^2 denotes a pseudo-R^2 based on the composite Bayesian model, R_b^2 shows the R^2 of the benchmark model (AR(1)). Unadjusted and (adjusted) R^2 ($\bar{R}^2$) are reported for the best 5 model specifications. The sample period is 01/1983-12/2010.

Table IA.6. Predictability FX Volatility ("Short"): Higher-order AR terms

Panel A.	*Composite Model*			Post.	Post.			*Top 5 Models*				
EUR	No.	Variable	$\pi\|y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.378	0.067	5.64		1	1	1	1	1
	2	AFD	**0.88**	0.049	0.025	1.93		1	1	1	1	1
	3	INFM	**0.68**	-0.032	0.027	-1.19		1	1	1	0	1
	4	RV(t-2)	**0.60**	0.086	0.086	1.01		1	1	0	1	0
	5	IPM	0.49	-0.022	0.027	-0.80		0	0	1	1	0
	6	INFA	0.48	0.021	0.026	0.82		1	1	1	0	1
	7	CRB	0.48	-0.019	0.024	-0.81		0	0	0	1	0
	8	CAP	0.28	-0.010	0.023	-0.46		1	0	0	0	1
	R_a^2	0.403					R^2	0.390	0.388	0.375	0.374	0.374
	R_b^2	0.313					$\bar{R}^2$	0.378	0.377	0.365	0.364	0.364
Panel B.	*Composite Model*			Post.	Post.			*Top 5 Models*				
JPY	No.	Variable	$\pi\|y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**0.98**	0.208	0.071	2.93		1	1	1	1	1
	2	BAS	**0.95**	0.084	0.031	2.74		1	1	1	1	1
	3	DIFF	**0.93**	-0.074	0.036	-2.05		1	1	1	1	1
	4	TED	**0.83**	0.051	0.031	1.67		1	1	1	1	1
	5	T-B	**0.74**	-0.065	0.046	-1.43		1	1	1	1	1
	6	C-P	**0.56**	-0.029	0.030	-0.96		0	0	1	1	1
	7	E-P	0.27	-0.017	0.032	-0.53		0	0	0	0	0
	8	C-T	0.24	-0.008	0.017	-0.48		0	0	1	0	0
	R_a^2	0.332					R^2	0.316	0.327	0.299	0.339	0.313
	R_b^2	0.219					$\bar{R}^2$	0.303	0.313	0.289	0.323	0.300
Panel C.	*Composite Model*			Post.	Post.			*Top 5 Models*				
GBP	No.	Variable	$\pi\|y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.378	0.067	5.64		1	1	1	1	1
	2	RV(t-2)	**0.88**	0.049	0.025	1.93		1	1	1	1	1
	3	AFD	**0.68**	-0.032	0.027	-1.19		1	1	1	1	1
	4	H-S	**0.60**	0.086	0.086	1.01		1	1	1	1	0
	5	M1M	0.49	-0.022	0.027	-0.80		1	1	1	1	1
	6	INFA	0.48	0.021	0.026	0.82		1	1	0	1	0
	7	TED	0.48	-0.019	0.024	-0.81		0	0	1	1	1
	8	M1A	0.28	-0.010	0.023	-0.46		0	1	0	1	0
	R_a^2	0.519					R^2	0.510	0.500	0.508	0.498	0.516
	R_b^2	0.432					$\bar{R}^2$	0.500	0.491	0.497	0.489	0.504
Panel D.	*Composite Model*			Post.	Post.			*Top 5 Models*				
CHF	No.	Variable	$\pi\|y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
	1	RV(t-1)	**1.00**	0.277	0.064	4.33		1	1	1	1	1
	2	AFD	**0.97**	0.058	0.021	2.81		1	1	1	1	1
	3	RV(t-2)	**0.88**	0.153	0.080	1.92		1	1	1	1	1
	4	CAP	0.48	-0.021	0.027	-0.77		1	1	0	1	0
	5	IPM	0.44	-0.020	0.028	-0.74		0	0	1	0	1
	6	CRB	0.41	-0.014	0.020	-0.71		0	0	0	1	0
	7	TED	0.32	0.011	0.020	0.58		1	0	0	0	1
	8	INFM	0.30	-0.010	0.017	-0.56		0	0	0	0	0
	R_a^2	0.340					R^2	0.324	0.322	0.309	0.309	0.322
	R_b^2	0.249					$\bar{R}^2$	0.314	0.312	0.300	0.300	0.312

Notes: This table reports in-sample predictability results for foreign exchange volatility for several major exchange rates vis-a-vis USD based on a Bayesian Model Averaging approach with a MC^3 algorithm. Additional AR terms (RV(t-2) and RV(t-3)) are included as predictors in the model search besides one lag of the dependent variable (RV(t-1)). The results display the results for the best 8 predictors, as ranked according to the posterior probability of inclusion $\pi|y$ (sorted in descending order). Moreover the table reports posterior means, standard deviation and BMA t-ratios of the best predictors (reflecting model uncertainty). Inclusion of the specific variable in the Top 5 models (according to the posterior model probability) is indicated by 1. R_a^2 denotes a pseudo-R^2 based on the composite Bayesian model, R_b^2 shows the R^2 of the benchmark model (AR(1)). Unadjusted and (adjusted) R^2 ($\bar{R}^2$) are reported for the best 5 model specifications. The sample period is 01/1983-12/2010.

Table IA.7. Classical Model Selection – Several Asset Classes: Higher-Order AR terms

A. FX-Aggr.	(i)	(ii)	(iii)	***B. Bonds***	(i)	(ii)	(iii)	***C. Stocks***	(i)	(ii)	(iii)	***D. Commod.***	(i)	(ii)	(iii)
RV(t-1)	**0.39**	**0.37**	**0.42**	RV(t-1)	**0.38**	**0.43**	**0.40**	RV(t-1)	**0.34**	**0.33**	**0.37**	RV(t-1)	**0.46**	**0.42**	**0.44**
	7.98	7.21	8.39		7.26	8.12	8.02		5.82	5.57	6.19		9.51	7.77	9.67
RV(t-2)	**0.19**	**0.14**		RV(t-2)				RV(t-2)	**0.19**	**0.19**	**0.22**	RV(t-2)	**0.27**	**0.22**	**0.28**
	3.85	2.53							3.42	3.46	3.99		5.76	4.19	5.88
RV(t-3)		**0.11**	**0.16**	RV(t-3)	**0.15**	**0.19**	**0.16**	RV(t-3)	**0.19**	**0.17**	**0.18**	RV(t-3)		**0.11**	
		2.19	3.61		2.38	3.14	2.72		4.19	3.73	3.74			2.21	
AFD	**0.08**	**0.08**	**0.08**	DEF	**0.06**	**0.06**	**0.05**	D-P	**-0.06**	**-0.06**		D-P	**-0.06**	**-0.06**	**-0.06**
	4.44	4.36	4.55		3.89	3.48	2.80		-3.83	-3.94			-3.53	-3.12	-3.80
TED	**0.07**	**0.07**	**0.07**	T-S	**0.04**			TED	**0.06**	**0.05**		CRB			-0.03
	5.32	5.34	5.64		2.44				2.10	2.14					-1.55
IPM	**-0.05**	**-0.05**	**-0.05**	M1A			**0.04**	IPM		**-0.04**		H-S	**-0.06**	**-0.06**	**-0.06**
	-3.68	-3.51	-3.78				2.12			-2.03			-4.18	-4.03	-4.21
				TURN	**-0.05**	**-0.05**	**-0.05**	MKT	**-0.07**	**-0.07**	**-0.08**				
					-3.01	-3.12	-3.12		-3.77	-4.06	-4.18				
								CAP			-0.04				
											-1.85				
								STR	**-0.05**	**-0.04**	**-0.05**				
									-3.58	-3.62	-3.60				
R^2	0.53	0.53	0.52	R^2	0.435	0.425	0.433	R^2	0.601	0.607	0.593	R^2	0.664	0.669	0.667
$\bar{R}^2$	0.52	0.52	0.52	$\bar{R}^2$	0.427	0.418	0.425	$\bar{R}^2$	0.592	0.597	0.585	$\bar{R}^2$	0.660	0.664	0.662
BIC	-2.49	-2.48	-2.48	BIC	-2.508	-2.507	-2.504	BIC	-2.348	-2.346	-2.345	BIC	-2.517	-2.513	-2.508

Notes: The table shows results of in-sample predictive regressions for aggregate FX volatility, U.S. bond market volatility, equity market volatility (short sample) and commodity market volatility based on a classical model selection approach. The benchmark specification allows for three possible lags of the dependent variable (RV(t-1), RV(t-2), RV(t-3)) in the model search. Predictive regressions results for the three top-performing models (based upon the BIC) are reported. Significant coefficients (at the 5% level based on HAC standard errors) are bold-printed and the corresponding classical t-statistics are reported below. Unadjusted (adjusted) R^2 ($\bar{R}^2$) are reported for the best 3 model specifications. The sample period is 01/1983-12/2010.

Table IA.8. Classical Model Selection - FX Market Volatility, Individual Currencies

A. GBP	(i)	(ii)	(iii)	***B. CHF***	(i)	(ii)	(iii)	***C. JPY***	(i)	(ii)	(iii)	***D. EUR***	(i)	(ii)	(iii)
RV(t-1)	**0.41**	**0.43**	**0.40**	RV(t-1)	**0.35**	**0.32**	**0.35**	RV(t-1)	**0.33**	**0.36**	**0.35**	RV(t-1)	**0.44**	**0.43**	**0.41**
	7.51	7.69	7.22		5.79	5.61	5.98		5.21	5.71	5.90		7.54	7.39	7.36
AFD	**0.05**	**0.04**	**0.06**	AFD	**0.06**	**0.05**	**0.07**	DIFF	**-0.06**	**-0.07**		AFD	**0.06**	**0.05**	**0.04**
	2.37	2.26	2.82		3.78	3.14	3.94		-3.38	-4.10			3.06	2.81	2.28
TED			**0.04**					E-P	**-0.05**		**-0.06**				
			2.52						-3.25		-3.63				
H-S	**-0.05**	**-0.07**	**-0.05**	CRB	**-0.04**	**-0.04**	**-0.04**					CRB	**-0.05**	**-0.04**	**-0.05**
	-4.03	-4.82	-3.38		-3.61	-3.56	-3.34						-3.85	-3.32	-4.11
D-P	**0.07**	**0.06**	**0.06**	CAP		**-0.05**	**-0.04**	CAP			**-0.05**	INFM		**-0.03**	
	4.44	4.08	3.42			-4.48	-3.96				-2.19			-2.65	
M1M	**0.05**	**0.06**	**0.05**	M1A		**0.04**						M1A			**0.03**
	3.23	3.59	3.15			2.51									2.00
IPM	**-0.04**		**-0.04**	IPM	**-0.05**							IPM	**-0.05**	**-0.04**	**-0.05**
	-2.95		-2.98		-4.14								-3.69	-3.44	-3.81
R^2	0.476	0.466	0.484	R^2	0.298	0.308	0.295	R^2	0.235	0.218	0.230	R^2	0.358	0.366	0.365
$\bar{R}^2$	0.467	0.458	0.472	$\bar{R}^2$	0.290	0.297	0.287	$\bar{R}^2$	0.228	0.213	0.223	$\bar{R}^2$	0.350	0.357	0.356
BIC	-2.549	-2.547	-2.546	BIC	-2.720	-2.716	-2.716	BIC	-2.332	-2.327	-2.326	BIC	-2.653	-2.649	-2.647

Notes: The table shows results of in-sample predictive regressions foreign exchange volatility for several major exchange rates vis-a-vis USD (short sample) based on a classical model selection approach. The benchmark specification allows for three lags of the dependent variable (RV(t-1), RV(t-2), RV(t-3)) in the model search. Predictive regressions results for the three top-performing models (based upon the BIC) are reported. Significant coefficients (at the 5% level based on HAC standard errors) are bold-printed and the corresponding classical t-statistics are reported below. Unadjusted (adjusted) R^2 ($\bar{R}^2$) are reported for the best 3 model specifications. The sample period is 01/1983-12/2010.

Table IA.9. Classical Model Selection - FX Market Volatility, Higher-Order AR terms

A. GBP	(i)	(ii)	(iii)	***B. CHF***	(i)	(ii)	(iii)	***C. JPY***	(i)	(ii)	(iii)	***D. EUR***	(i)	(ii)	(iii)
RV(t-1)	**0.33**	**0.34**	**0.33**	RV(t-1)	**0.28**	**0.28**	**0.29**	RV(t-1)	**0.28**	**0.29**	**0.30**	RV(t-1)	**0.37**	**0.35**	**0.35**
	6.11	6.61	6.25		5.22	5.35	5.23		4.74	5.11	5.60		7.16	6.73	6.91
RV(t-2)	**0.23**	**0.25**	**0.24**	RV(t-2)	**0.17**	**0.17**	**0.18**	RV(t-2)	**0.17**	**0.16**	**0.18**	RV(t-2)	**0.14**	**0.15**	**0.14**
	5.41	5.68	5.51		3.24	3.28	3.450		3.53	3.38	3.79		2.84	2.95	2.88
AFD	**0.05**	**0.05**	**0.05**	AFD	**0.06**	**0.06**	**0.06**	AFD	**0.04**	**0.05**	**0.05**	AFD	**0.05**	**0.06**	**0.06**
	2.84	2.71	2.81		3.76	3.95	3.48		2.16	2.15	2.32		3.11	3.36	3.55
TED	**0.06**	**0.07**	**0.06**	CRB	**-0.04**	**-0.04**		C-T	**-0.04**			TED		**0.04**	**0.03**
	4.16	4.84	4.95		-3.33	-3.05			-2.37					3.19	2.59
H-S	**-0.04**			CAP		**-0.04**		CAP			**-0.06**	CRB	**-0.05**		**-0.04**
	-3.14					-3.83					-2.71		-3.64		-3.06
M1M	**0.05**	**0.05**	**0.04**	INFM			**-0.03**	DIFF	**-0.06**	**-0.06**		INFM		**-0.04**	
	3.60	3.66	3.12				-2.42		-4.21	-4.03				-3.40	
IPM			**-0.04**	IPM	**-0.05**		**-0.05**					IPM	**-0.04**	**-0.04**	**-0.04**
			-3.05		-4.00		-3.56						-3.27	-2.60	-2.99
R^2	0.498	0.487	0.495	R^2	0.324	0.322	0.321	R^2	0.270	0.257	0.257	R^2	0.374	0.384	0.384
$\bar{R}^2$	0.489	0.479	0.486	$\bar{R}^2$	0.314	0.312	0.311	$\bar{R}^2$	0.259	0.248	0.247	$\bar{R}^2$	0.364	0.372	0.372
BIC	-2.587	-2.583	-2.582	BIC	-2.737	-2.733	-2.732	BIC	-2.338	-2.338	-2.337	BIC	-2.655	-2.654	-2.654

Notes: The table shows results of in-sample predictive regressions for foreign exchange volatility for several major exchange rates vis-a-vis USD (short sample) based on a classical model selection approach. The benchmark specification allows for three lags of the dependent variable in the model search. Predictive regressions results for the three top-performing models (based upon the BIC) are reported. Significant coefficients (at the 5% level based on HAC standard errors) are bold-printed and the corresponding classical t-statistics are reported below. Unadjusted (adjusted) R^2 ($\bar{R}^2$) are reported for the best 3 model specifications. The sample period is 01/1983-12/2010.

Table IA.10. Volatility Forecasting Results – Quarterly Frequency

	Stocks ("Long")			
	A.		B.	
5 Top Variables		$\pi\|y$		$\pi\|y$
(i)	RV(t-1)	**1.00**	RV(t-1)	**1.00**
(ii)	DEF	**1.00**	RV(t-2)	**1.00**
(iii)	E-P	**0.51**	DEF	**0.62**
(iv)	RBR	0.31	RBR	0.28
(v)	LTR	0.27	LTR	0.21
ΔR^2		3.30		1.23
	Aggregate FX ("Short")			
	A.		B.	
5 Top Variables		$\pi\|y$		$\pi\|y$
(i)	RV(t-1)	**1.00**	RV(t-1)	**1.00**
(ii)	TED	**0.64**	TED	**0.73**
(iii)	TURN	**0.57**	TURN	**0.62**
(iv)	IPM	0.29	RV(t-2)	**0.57**
(v)	M1M	0.26	M1M	0.42
ΔR^2		12.00		11.50
	Bonds ("Short")			
	A.		B.	
5 Top Variables		$\pi\|y$		$\pi\|y$
(i)	RV(t-1)	**1.00**	RV(t-1)	**1.00**
(ii)	M1A	**0.53**	TED	**0.55**
(iii)	TED	**0.52**	M1A	0.43
(iv)	STR	0.48	AFD	0.43
(v)	AFD	0.38	STR	0.42
ΔR^2		9.20		8.45
	Equities ("Short")			
	A.		B.	
5 Top Variables		$\pi\|y$		$\pi\|y$
(i)	RV(t-1)	**1.00**	TED	**1.00**
(ii)	TED	**1.00**	RV(t-1)	**1.00**
(iii)	D-P	**0.95**	D-P	**1.00**
(iv)	E-P	**0.64**	RV(t-2)	**0.85**
(v)	STR	**0.63**	STR	**0.78**
ΔR^2		15.20		15.70
	Commodities ("Short")			
	A.		B.	
5 Top Variables		$\pi\|y$		$\pi\|y$
(i)	RV(t-1)	**1.00**	RV(t-1)	**1.00**
(ii)	D-P	**0.58**	C-P	**0.54**
(iii)	C-P	0.46	D-P	**0.46**
(iv)	LTR	0.44	LTR	0.39
(v)	IPM	0.34	IPM	0.36
ΔR^2		7.20		6.75

Notes: The table reports results from in-sample predictive regressions at a quarterly frequency and forecast horizon. The top five predictors in terms of posterior inclusion probability $\pi|y$ are reported. Panel A shows results where one AR(1) term is included, whereas Panel B allows for possibly two autoregressive lags of the quarterly RV series. ΔR^2 represents the difference in the pseudo-R^2 of the composite Bayesian model and the R^2 of the autoregressive benchmark.

Table IA.11. Forecast Evaluation: Equity Volatility ("Long"), AR(3) Benchmark

	BIC	AIC	R^2	BMA	MC^3	EW
Start: 01/1937						
Theil's U	0.976	0.970	0.970	0.975	0.977	0.972
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.00	0.00	0.00	0.00	0.00	0.00
R^2_{OOS}	0.047	0.059	0.059	0.049	0.047	0.055
GW stat.	2.40	2.81	2.77	2.59	2.31	2.91
MZ GLS p-val.	0.05	0.10	0.10	0.01	0.14	0.07
Start: 01/1957						
Theil's U	0.982	0.979	0.977	0.982	0.984	0.979
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.00	0.00	0.00	0.00	0.00	0.00
R^2_{OOS}	0.036	0.042	0.045	0.036	0.032	0.041
GW stat.	1.60	1.76	1.87	1.61	1.32	1.90
MZ GLS p-val.	0.07	0.04	0.03	0.03	0.39	0.09
Start: 01/1977						
Theil's U	0.973	0.966	0.966	0.969	0.969	0.970
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.00	0.00	0.00	0.00	0.00	0.00
R^2_{OOS}	0.054	0.066	0.066	0.061	0.061	0.059
GW stat.	1.83	2.21	2.23	2.16	2.19	2.15
MZ GLS p-val.	0.06	0.05	0.07	0.12	0.10	0.10

Notes: The table shows the results from the evaluation of out-of-sample forecasts based on various forecasting approaches: i) forecasts based on the model with the lowest Schwarz criterion at the forecast date (BIC), ii) forecast based on the model with the lowest Akaike criterion at the forecast date (AIC), iii) forecast from the model with highest adjusted R^2, iv) forecast from a BMA approach with analytical evaluation of posterior model probabilities, v) BMA forecasts based on the MC^3 sampling algorithm and vi) an equally weighted forecast of all evaluated models (EW). The benchmark is a AR(3) model. Results for different start dates of the forecasting scheme are provided: The forecasts start in 02/1993 after an initialization period of 10 years. The reported statistics include Theil's U which is the ratio of the RMSE of the model of interest and the RMSE of the benchmark model (TU), the out-of-sample R^2 of Campbell and Thompson (2008). $\#\text{TU}^{bs}<\text{TU}$ denotes the bootstrap p-value for testing equal predictive performance of the macro-finance augmented model and the AR(3) benchmark against the alternative of superior performance of the model including macro-finance predictors. The bootstrap procedure follows a model-based wild bootstrap methodology as described in section B.3 of the appendix. MZ GLS denotes the GLS version of the Mincer-Zarnowitz statistic and GW stat denotes the test statistic by Giacomini and White (2006).

Table IA.12. Forecast Evaluation: Other Asset Classes ("Short"), AR(3) Benchmark

	BIC	AIC	R^2	BMA	MC^3	EW
FX-Aggregate:						
Theil's U	1.026	1.009	0.990	1.015	1.024	1.004
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.51	0.12	0.03	0.63	0.466	0.25
R^2_{OOS}	-0.052	-0.018	0.020	-0.031	-0.049	-0.007
GW stat.	-0.67	-0.21	0.25	-0.42	-0.62	-0.09
MZ GLS p-val.	0.00	0.00	0.00	0.00	0.01	0.00
Bonds:						
Theil's U	1.008	1.000	0.989	1.002	1.006	0.998
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.18	0.07	0.04	0.18	0.11	0.08
R^2_{OOS}	-0.016	0.000	0.021	-0.004	-0.012	0.004
GW stat.	-0.32	0.00	0.46	-0.10	-0.26	0.08
MZ GLS p-val.	0.05	0.21	0.26	0.05	0.10	0.16
Stocks:						
Theil's U	1.001	0.963	0.967	0.973	1.007	0.974
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.06	0.00	0.02	0.00	0.18	0.00
R^2_{OOS}	-0.002	0.074	0.065	0.053	-0.014	0.052
GW stat.	-0.05	1.04	0.91	1.24	-0.16	1.35
MZ GLS p-val.	0.64	0.92	0.80	0.96	0.00	0.85
Commodities:						
Theil's U	1.007	1.009	0.995	0.992	1.015	1.007
$\#\widehat{TU}_{bs} < \widehat{TU}$	0.16	0.16	0.05	0.05	0.37	0.43
R^2_{OOS}	-0.013	-0.018	0.010	0.017	-0.030	-0.014
GW stat.	-0.49	-0.53	0.26	0.67	-1.25	-0.55
MZ GLS p-val.	0.00	0.00	0.00	0.02	0.00	0.00

Notes: The table shows the results from the evaluation of out-of-sample forecasts based on various forecasting approaches: i) forecasts based on the model with the lowest Schwarz criterion at the forecast date (BIC), ii) forecast based on the model with the lowest Akaike criterion at the forecast date (AIC), iii) forecast from the model with highest adjusted R^2, iv) forecast from a BMA approach with analytical evaluation of posterior model probabilities, v) BMA forecasts based on the MC^3 sampling algorithm and vi) an equally weighted forecast of all evaluated models (EW). The benchmark is a AR(3) model. Results for different start dates of the forecasting scheme are provided: The forecasts start in 02/1993 after an initialization period of 10 years. The reported statistics include Theil's U which is the ratio of the RMSE of the model of interest and the RMSE of the benchmark model (TU), the out-of-sample R^2 of Campbell and Thompson (2008). $\#TU^{bs}<TU$ denotes the bootstrap p-value for testing equal predictive performance of the macro-finance augmented model and the AR(3) benchmark against the alternative of superior performance of the model including macro-finance predictors. The bootstrap procedure follows a model-based wild bootstrap methodology as described in section B.3 of the appendix. MZ GLS denotes the GLS version of the Mincer-Zarnowitz statistic and GW stat denotes the test statistic by Giacomini and White (2006).

Table IA.13. Equity Volatility Forecasting – Considering Implied Volatility and Belief Dispersion

Panel A.											
Composite Model			Post.	Post.			*Top 5 Models*				
No.	Variable	$\pi\|y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
1	VIX	**1.00**	0.338	0.087	3.89		1	1	1	1	1
2	DP	**0.94**	-0.084	0.032	-2.60		1	1	1	1	1
3	DISPI	0.50	0.032	0.038	0.85		0	1	1	1	1
4	TED	0.46	0.025	0.032	0.79		0	0	1	0	0
5	IPM	0.45	-0.039	0.072	-0.54		1	1	0	1	1
6	MKT	0.27	-0.013	0.024	-0.51		0	0	0	0	1
7	AFD	0.26	0.012	0.025	0.50		0	0	0	0	0
8	STR	0.25	-0.010	0.019	-0.50		0	0	0	1	0
R_a^2	0.713					R^2	0.688	0.688	0.696	0.695	0.703
R_b^2	0.586					$\bar{R}^2$	0.684	0.684	0.691	0.690	0.697

Panel B.											
Composite Model			Post.	Post.			*Top 5 Models*				
No.	Variable	$\pi\|y$	Mean	STD	t-ratio		(i)	(ii)	(iii)	(iv)	(v)
1	VIX	**1.00**	0.339	0.062	5.42		1	1	1	1	1
2	D-P	**0.97**	-0.074	0.027	-2.71		1	1	1	1	1
3	IPM	**0.66**	-0.055	0.063	-0.88		1	1	0	1	1
4	TED	0.39	0.020	0.030	0.68		0	0	1	0	1
5	INFA	0.39	0.020	0.030	0.67		0	0	1	1	0
6	AFD	0.34	0.017	0.028	0.60		0	0	1	0	0
7	ORDA	0.30	-0.017	0.030	-0.55		0	0	1	0	0
8	MKT	0.27	-0.012	0.025	-0.48		1	0	0	0	0
R_a^2	0.665					R^2	0.690	0.697	0.697	0.711	0.696
R_b^2	0.632					$\bar{R}^2$	0.686	0.692	0.692	0.704	0.691

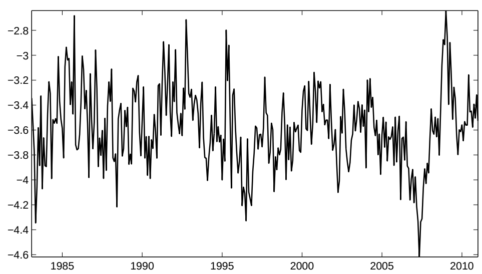
Notes: This table reports in-sample predictability results for U.S. equity market volatility (short sample) considering the role of implied volatility (VIX) and forecaster uncertainty about future GDP growth (DISPGDP) and inflation (DISPINF). Results are based on a Bayesian Model Averaging approach with a MC^3 algorithm. The results are obtained with a set of predictors which contains the lagged dependent variable RV(t-1) in Panel A, results based on a benchmark with higher order AR terms are reported Panel B. The results display the results for the best 8 predictors, as ranked according to the posterior probability of inclusion $\pi|y$ (sorted in descending order). Moreover the table reports posterior means, standard deviation and BMA t-ratios of the best predictors (reflecting model uncertainty). Inclusion of the specific variable in the Top 5 models (according to the posterior model probability) is indicated by 1. R_a^2 denotes a pseudo-R^2 based on the composite Bayesian model, R_b^2 shows the R^2 of the benchmark model (AR(1)). Unadjusted (adjusted) R^2 ($\bar{R}^2$) are reported for the best 5 model specifications. The sample period is 01/1983-12/2010.

Table IA.14. Equity Volatility Forecasting – Absolute Values and Non-Linearities

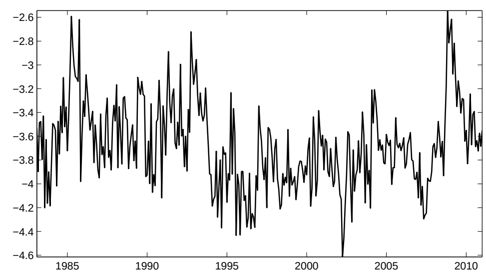
Absolute Values					**Incl. Squared Terms**				
	A.		B.			A.		B.	
5 Top Var.		$\pi\|y$		$\pi\|y$	5 Top Var.		$\pi\|y$		$\pi\|y$
(i)	RV(t-1)	**1.00**	RV(t-1)	**1.00**	(i)	RV(t-1)	**1.00**	RV(t-1)	**1.00**
(ii)	MKT	**0.90**	MKT	**1.00**	(ii)	DEF (lv)	**1.00**	RV(t-2)	**1.00**
(iii)	INFM	**0.85**	RV(t-2)	**1.00**	(iii)	MKT (lv)	**1.00**	MKT (lv)	**1.00**
(iv)	D-P	**0.71**	RV(t-3)	**0.98**	(iv)	E-P (lv)	**0.87**	DEF (lv)	**1.00**
(v)	DEF	**0.68**	INFM	**0.70**	(v)	STR (lv)	**0.86**	RV(t-3)	**0.94**
ΔR^2		1.96		1.30	ΔR^2		4.56		3.74

Notes: This table reports in-sample predictability results for U.S. equity market volatility (short sample) considering the absolute values of predictors (Panel A) and non-linearities (incl. squared predictors, Panel B). Results are based on a Bayesian Model Averaging approach with a MC^3 algorithm. The results are obtained with a set of predictors which contains the lagged dependent variable RV(t-1) in Panel A, results based on a benchmark with higher order AR terms are reported Panel B. The results display the results for the best 8 predictors, as ranked according to the posterior probability of inclusion $\pi|y$ (sorted in descending order). Moreover the table reports posterior means, standard deviation and BMA t-ratios of the best predictors (reflecting model uncertainty). Inclusion of the specific variable in the Top 5 models (according to the posterior model probability) is indicated by 1. R_a^2 denotes a pseudo-R^2 based on the composite Bayesian model, R_b^2 shows the R^2 of the benchmark model (AR(1)). Unadjusted (adjusted) R^2 ($\bar{R}^2$) are reported for the best 5 model specifications. The sample period is 01/1983-12/2010.

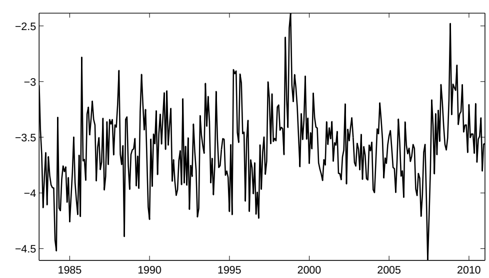
Figure IA.1. FX Volatility ("Short")



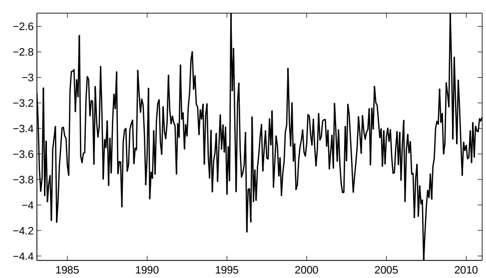
(a) EUR



(b) GBP



(c) JPY



(d) CHF

Notes: This figure shows (log) realized volatility for several major exchange rates against the USD over the short sample period from 01/1983-12/2010 ("Short").

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