Forecasting the Stock Return Distribution Using Macro-Finance Variables

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Contribution

Propose a New Method that can precisely predict the distribution of *S&P* 500 index return.

- **Make the First Attempt** to forecast the stock return distribution by combining quantile regression models with volatility-based models.
  access market risk, make optimal portfolio choices, option pricing, and delta hedging.
- **Uncover the Connection** between macro-finance variables and the stock return dynamics.

Motivation

- Need a precise estimate of the stock return distribution:

  hard to find a consistently superior model.

  seek answers from forecast combination.

- Contradictory findings on the predictive power of Macro-finance variables:

  ***pros**: French and Stambaugh (1987), and Campbell and Shiller (1988), Lettau and Ludvigson (2002)*.

  ***cons**: Welch and Goyal (2008), Bossaerts and Hillion (1999), Campbell and Thompson (2008), and Lettau and Van Nieuwerburgh (2008)*.

  ***new pros**: Cenesizoglu and Timmermann (2008): Macro-finance variables can predict other quantiles of the stock return density.*

Methodology

Two Steps:

1. First, combine density forecasts made by quantile regressions using 11 macro-finance variables or their principal components.
2. Second, combine these density forecasts with various volatility-based models. The combination rule is to maximize some indicator of the predictive accuracy.

The N **Macro-Finance Variables** are:

- ***Finance Variables:*** (1) dividends(**D**), (2) earnings(**E**), (3) stock variance(**svar**), (4) book-to-market ratio(**b/m**), (5) net equity expansion(**ntis**), (6) term spread(**tms**), (7) default yield spread(**dfy**).
- ***Macroeconomic Variables:*** (8) inflation(**infl**), (9) unemployment rate(**ume**), (10) industrial production growth(**ip**), (11) non-farm payroll(**nfp**).

Main Findings

Two Main Findings:

1. ***Density Forecasting***: The combined density forecast using both macro-finance variables and volatility-based models performs the best.
2. ***Portfolio Management***: The certainty equivalent return can be up to 0.35% per month higher than can be obtained with the EGARCH Student's-t model.

Outline

1. Model Specification and Estimation
2. Forecasting Combination and Comparison
3. Option Trading Implication
4. Portfolio Management Performance

Forecast Specification

- **Data:** Continuously compounded *S&P* 500 index return,

$$y_t = 100 \cdot \log(p_t/p_{t-1}).$$

- **Data Frequency:** Monthly.
- **Forecasting Method:** Recursive, Out-of-Sample.
- **Sample Period:** January, 1950 to December, 2011.
- **Forecasting Horizon:** One Month Ahead Forecast.

Forecasting Models

Models in Five Classes

*Conditioning on **Macro-Finance Variables***

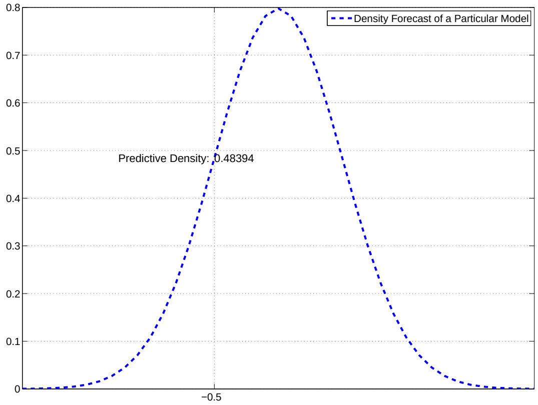
	Model Class	Features	Models
I	**Quantile density forecast: MF**	non-parametric, model combination	11
II	**Quantile density forecast: PCA**	non-parametric, single model	3

*Conditioning on **Return Information Alone***

	Model Class	Features	Models
III	**Exponential GARCH Models**	parametric, fat-tail, leverage effect	8
IV	**Stochastic Volatility Models**	better capture return-volatility relationship	4
V	**Realized Volatility Models**	semi-parametric; use high-frequency data	4

- **Measure of Predictive Accuracy:** the ***Log Predictive Likelihood***

Log Predictive Likelihood



- **Log Predictive Likelihood**: sum of the ***Log Predictive Density***.
- **Predictive Density**: *the higher, the better*.
- Parallel to **Root-Mean-Squared Error (RMSE)** for a point forecast.

Forecast Combination Rule

- **Optimal Prediction Pool:** parallel to optimal portfolio construction.
- **The Combination Objective:**
  To maximize the ***Log Predictive Likelihood***.
  1. The optimal pool typically includes a mix of models.
  2. Each model contributes a strength that balances some weakness of the other models entering the optimal pool.
  3. The rule fundamentally differs from ***Bayesian Model Averaging*** and ***Conventional Forecast Competition***.

Forecasting Models: Class I

I. Quantile Density Forecasts

- Each quantile of y_t is predicted by

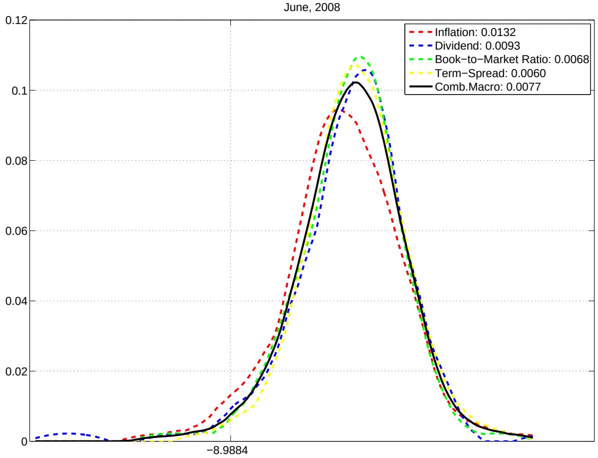
$$\hat{Q}_\tau(y_t|x_{i,t-1}) = \hat{\beta}_{i0}(\tau) + \hat{\beta}_{i1}(\tau)y_{t-1} + \hat{\beta}_{i2}(\tau)x_{i,t-1}. \quad \text{for } i = 1\ldots,N.$$

- Estimation of $\hat{\beta}_i$ (Koenker and Park (1996)): ***MM Algorithm***.
- A fine grid of quantiles: $\tau = 1\%, \ldots, 99\%$.
- Three ways to construct the predictive distribution.
  1. *non-parametric kernel smoothing.* ✓
  2. *direct method: finite sample, quantile crossing.* ×
  3. *interpolation: doesn't work in real-time* ×

▸ FORECAST COMBINATION

Forecast Combination: An Example

An Illustration of Forecast Combination



▸ FORECAST COMBINATION RULE

Forecasting Models: Class II

II. Three Single-Model Forecast:

- The First **r** Principal Components of $\underbrace{\mathbf{x}_{t-1}}_{N\times 1}$.

$$\hat{Q}_\tau(y_t|\mathbf{x}_{t-1}) = \hat{\beta}_0(\tau) + \hat{\beta}_1(\tau)y_{t-1} + \hat{\beta}_2(\tau)\underbrace{\mathbf{f}_{t-1}}_{\mathbf{r}\times 1}.$$

- **Ando and Tsay (2011) Quantile-Varying Factor**

$$\hat{Q}_\tau(y_t|\mathbf{x}_{t-1}) = \hat{\beta}_0(\tau) + \hat{\beta}_1(\tau)y_{t-1} + \hat{\beta}_2(\tau)\underbrace{\mathbf{f}_{\tau,t-1}}_{\mathbf{r}(\tau)\times 1}.$$

- Multivariate Forecast

$$\hat{Q}_\tau(y_t|\mathbf{x}_{t-1}) = \hat{\beta}_0(\tau) + \hat{\beta}_1(\tau)y_{t-1} + \hat{\beta}_2(\tau)\underbrace{\mathbf{x}_{t-1}}_{N\times 1}.$$

Forecasting Models: Class III

III. EGARCH models

$$\begin{aligned} y_t &= \mu_Y + \sigma_Y \exp(\sum_{i=1}^{k} h_{i,t}/2)\varepsilon_{j,t} \\ h_{i,t} &= \alpha_i h_{i,t-1} + \beta_i(|\varepsilon_{j,t-1}| - (2/\pi)^{1/2}) + \gamma_i \varepsilon_{j,t-1}. \end{aligned}$$

- $i, j = 1 \ldots, k$, and $k = 1, 2$: up to two volatility components.
- ε_t is ***Gaussian, Student's t*** or ***Generalized Error Distribution***.
- If $\gamma_i < 0$, the model captures the ***Leverage Effect***.

Forecasting Models: Class IV

IV. Stochastic Volatility (SVOL) Models

$$
\begin{aligned}
y_t &= \exp(h_t/2)\varepsilon_t, \\
h_t &= \mu + \phi(h_{t-1} - \mu) + \eta_t, \quad t = 1, \ldots, T. \\
\eta_t &= \rho\varepsilon_t + \sqrt{1-\rho^2}u_t, \quad u_t \sim N(0,1). \\
\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} &\mid (\rho, \sigma) \sim i.i.d. \ \ \mathcal{N}_2(0, \Sigma), \\
\Sigma &= \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}.
\end{aligned}
$$

- ***The Basic SVOL Model***: ε_t is Normal and $\rho = 0$.
- ***Fat-tailed SVOL Model***: ε_t follows a Student's-t distribution.
- ***The Correlated SVOL Model***: $\rho \neq 0$, ***Leverage Effect***.

Forecasting Models: Class V

V. Realized Volatility Model

The monthly variance is calculated using the equation.

$$\sigma_t^2 = \sum_{i=1}^{N_t} r_{it}^2 + 2\sum_{i=2}^{N_t} r_{it} r_{i-1t}.$$

σ_t^2 is then treated as the **Realized Volatility (RV)** in modeling the return:

$$y_{t+1} = \mu_t + \sigma_t \varepsilon_t, \tag{1}$$

$$\log \sigma_t^2 = \phi_0 + \phi_1 \log \sigma_{t-1}^2 + u_t. \tag{2}$$

- ϕ_0, and ϕ_1 are estimated via OLS. μ_t is estimated by MLE.
- ε_t may follow ***Gaussian, Student's t*** or ***Generalized Error Distribution***.

Forecast Comparison: Predictive Accuracy

Table.1. Predictive Likelihood of Density Forecasts in Five Classes

Sample Periods 1959 : 01 — 2011 : 12

Class	Combined Forecasts	Individual Forecasts			
I	**Combined Macro-Finance Variables** 76.51 (3rd)	*Dividend* 51.99	*Earnings* 54.56	*SVAR* 72.73	*Book to Mkt Ratio* 67.80
		Net Equity Exp. 67.60	*Term Spread* 67.96	*Default Yield Spread* 75.90	*Inflation* 66.61
		Unemployment Rate 70.50	*Industrial Production* 77.93	*Non-farm Payroll* 78.13	
II	**Single-Model Multivariate Forecasts**	*Ando-Tsay Factor* 66.20	*1st. P.C.* 58.89	*Multivariate* −7.65	
III	**Combined EGARCHs** 53.28	*Gaussian* (1, 1) 39.48	*Gaussian* (1, 2) 31.53	*Gaussian* (2, 1) 22.44	*Gaussian* (2, 2) 37.31
		Student-t (1, 1) 0.00	*Student-t* (2, 1) 2.86	*GED* (1, 1) 15.74	*GED* (2, 1) −13.75
IV	**Combined SVs** 61.75	*Gaussian SV* 59.38	*Fat-tail SV* 60.00	*Corr SV* 64.99	*Fat-tail Corr SV* 55.82
V	**Combined RVs** 89.99 (2nd)	*RV-Gaussian* (1) 33.09	*RV-Gaussian* (2) 32.71	*RV-Student's t* 55.68	*RV-GED* 20.39
	Combine All 30 models 90.62 (1st)				

Note: The higher is the predictive likelihood, the more precise is the forecast.

Forecast Comparison: Test Results I

Table.2.a Test Results: Combined Density Forecasts

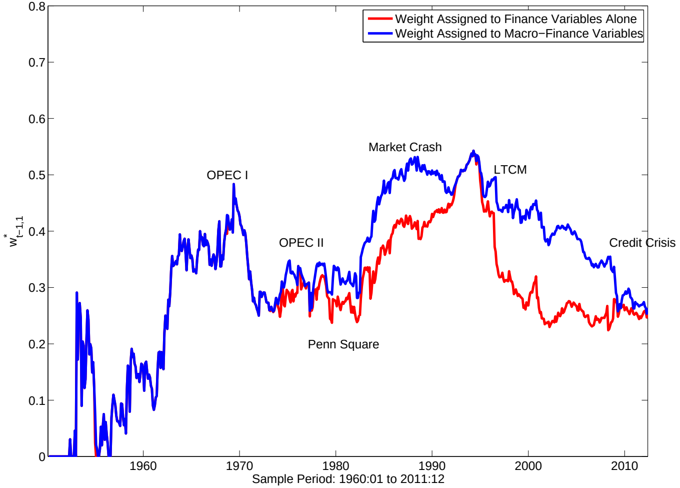
Sample Periods 1959 : 01 — 2011 : 12

Models	Comb.RV	Comb.MF	ATIC	Comb.SV	1st.PC	Comb.EGARCH	Multivariate
Comb.All	0.11	2.07	2.67	2.84	3.71	4.07	5.48
Asy. p-value	(0.46)	(0.02*)	(0.00*)	(0.00*)	(0.00*)	(0.00*)	(0.00*)
Boot. p-value	[0.46]	[0.02*]	[0.01*]	[0.01*]	[0.00*]	[0.00*]	[0.00*]
Comb.RV		1.37	2.23	2.58	3.02	3.22	4.75
Asy. p-value		(0.09)	(0.01*)	(0.00*)	(0.00*)	(0.00*)	(0.00*)
Boot. p-value		[0.08]	[0.02*]	[0.01*]	[0.00*]	[0.00*]	[0.00*]
Comb.MF			1.41	1.27	2.10	2.14	4.73
Asy. p-value			(0.08)	(0.10)	(0.02*)	(0.02*)	(0.00*)
Boot. p-value			[0.08]	[0.11]	[0.02*]	[0.02*]	[0.00*]
ATIC. Factor				0.41	1.15	1.13	3.78
Asy. p-value				(0.34)	(0.12)	(0.13)	(0.00*)
Boot. p-value				[0.34]	[0.11]	[0.12]	[0.00*]
Comb.SV					0.26	0.70	3.33
Asy. p-value					(0.40)	(0.24)	(0.00*)
Boot. p-value					[0.39]	[0.22]	[0.00*]

Note: When the sample stops at December, 2008, and the comparison is set between *Comb.All* and *Comb.RV*, the ▸ Amisano and Giacomini (2007) Test Statistic is positive and significant, in favor of *Comb.All*. When the comparison is set between *Comb.All* and any individual model, AG test-stat is always positive and significant. ▸ detail

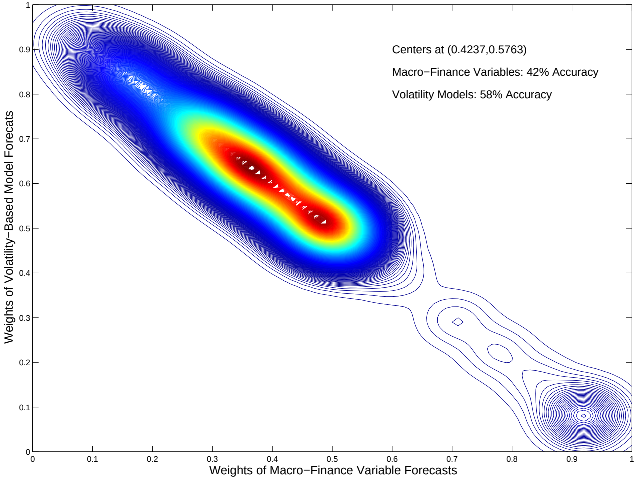
Predictive Accuracy Contribution

Weight of Macro-Finance Variables in Comb.All



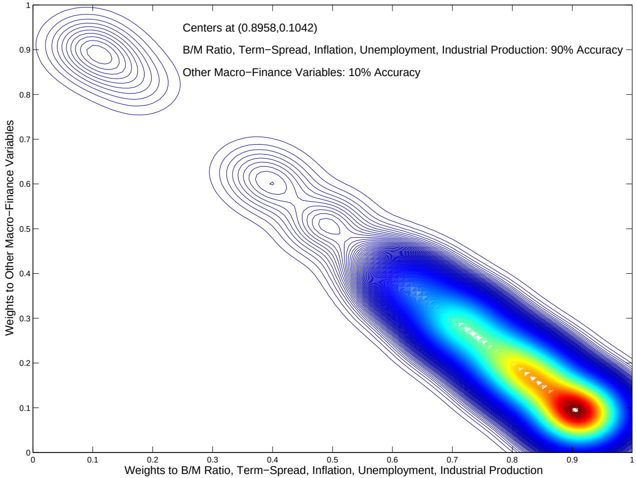
Predictive Accuracy Contribution

Comb.All



Predictive Accuracy Contribution

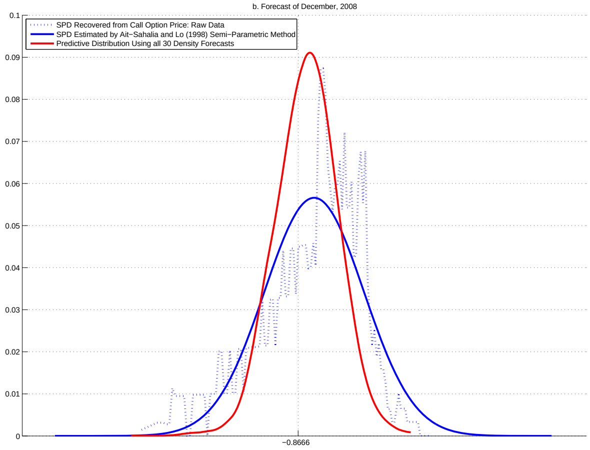
Comb.Macro



Physical Density vs. Risk Neutral Density

The Difference Reflects the Risk Premium

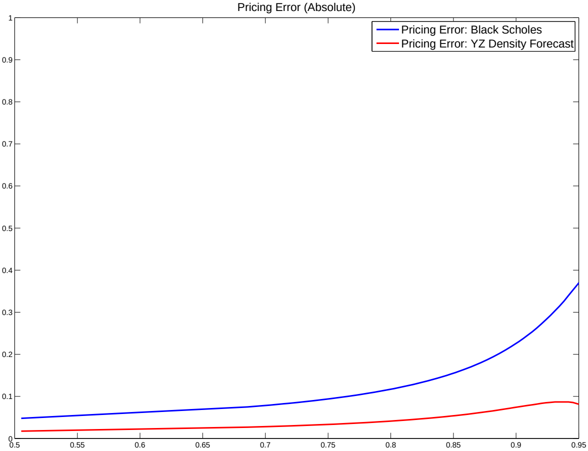
at the End of November, 2008



Comparison of Pricing Error

The Pricing Error of Comb.All is Smaller

April, 2008



An Asset Pricing Model

An investor maximizes

$$
\begin{aligned}
U(W_{t+1}) &= \frac{W_{t+1}^{1-\gamma}}{1-\gamma}, \\
W_{t+1} &= W_t + a_t W_t R_{t+1} + (1-a_t) W_t R_{f,t} \\
&\equiv W_t\left(1 + a_t R_{t+1}^e + R_{f,t}\right).
\end{aligned}
$$

- ***no short-sale case***: $0 \leq a_t \leq 1$
- ***short-sale allowed case***: $a_t \leq 0$, two types of margin restriction.
- ***risk aversion*** level γ ranges from 1 to 200.

Optimal Portfolio Weight

Portfolio weights at the end of month t:

$$a_t^* = \arg\max_{a_t} \int_{-\infty}^{+\infty} \underbrace{\frac{[W_t(1 + a_t R_{t+1}^e + R_{f,t})]^{1-\gamma}}{1-\gamma}}_{\text{Utility Function}} \underbrace{f(R_{t+1}^e | \mathcal{F}_t)}_{} dR_{t+1}^e.$$

▸ Density of Excess Return

$$= \arg\max_{a_t} \sum_{i=1}^{\mathbf{S}} \frac{[W_t(1 + a_t R_{t+1}^e + R_{f,t})]^{1-\gamma}}{1-\gamma} P(\mathbf{r}_{i-1} < R_{t+1}^e \leq \mathbf{r}_i | \mathcal{F}_t).$$

- a_t^* is chosen to ***Maximize the Expected Utility***.
- $[\mathbf{r}_0, \ldots, \mathbf{r}_{i-1}, \mathbf{r}_i, \ldots, \mathbf{r}_\mathbf{S}]$ is a sequence of possible realizations of R_{t+1}^e.

Margin Restriction on Short Sale

When the **Short-Sale** is permitted, two types of **Margin Restriction**:

I. $\mathbf{-1 \leq a_t^* \leq 1}$: $a_t^* < 0$ means that the investor short sells shares at t to invest in risk-free asset. $a_t^* \geq -1$ implies that the value of shares borrowed at t cannot exceed the the investor's wealth.

II. **A maintenance margin of** 50%: the equity in the investor's account must be at least 50% of the value of her short-position.

$$\frac{\overbrace{(1-a_t)W_t(1+R_{f,t})}^{\text{Asset at } (t+1) \text{ end}} - \overbrace{(\frac{-a_t W_t}{P_t}) \cdot E_t(P_{t+1})}^{\text{Expected Value of Shares (Liability)}}}{\underbrace{(\frac{-a_t W_t}{P_t}) \cdot E_t(P_{t+1})}_{\textit{Liability}}} \geq 50\%.$$

Measure the Economic Gain

- Optimal portfolio weights, a_t^*, give rise to a realized utility next period

$$U(W_{t+1}^*) = \frac{[W_t(1 + a_{t+1}^* R_{t+1}^e + R_{f,t})]^{1-\gamma}}{1-\gamma}.$$

- The economic value of the density forecasts can be measured by the **Certainty Equivalent Rate of Return (CER)**:

$$CER = \left[(1-\gamma)\frac{1}{T-q}\sum_{t=q+1}^{T} U(W_t^*)\right]^{1/(1-\gamma)} - 1.$$

Three Representative Forecasts

A. **Comb.MF**: the combined forecast of macro-finance variables
- uses information from Macro-finance variables alone
- combines multiple non-parametric data generating processes.

B. **Comb.RV**: the combined forecast of realized volatility models
- has the best performance among all volatility-based models.
- uses return information alone
- combines multiple parametric data generating processes.

C. **Comb.All**: the combined forecast of all 30 models
- combines multiple data generating processes as well as various sources of information.

Three Representative Forecasts

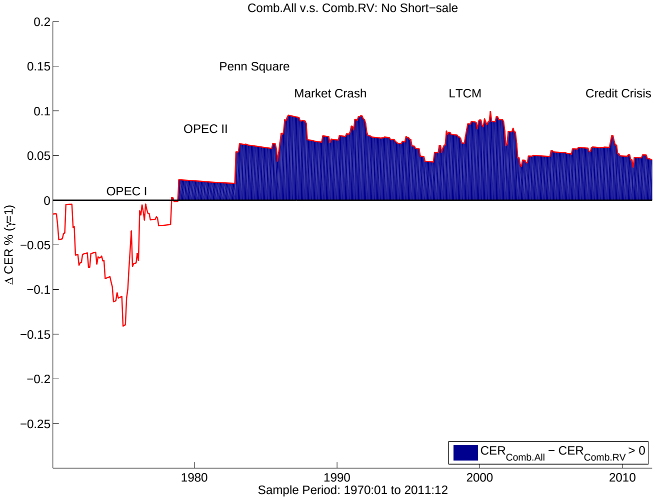
Table.3.a The Difference in CER by 2011 December (% per month)

Models	Strategy	Risk Aversion $\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 10$	$\gamma = 100$
Comb.All	*no short-sale*	0.16	0.13	0.13	0.11	0.10	0.05	0.00
	short-sale	0.35	0.27	0.27	0.25	0.23	0.13	0.00
	(margin = 0.5)	0.33	0.25	0.25	0.23	0.20	0.01	0.00
Comb.RV	*no short-sale*	0.11	0.12	0.11	0.09	0.08	0.04	0.00
	short-sale	0.26	0.29	0.27	0.25	0.22	0.12	0.01
	(margin = 0.5)	0.25	0.28	0.27	0.25	0.20	0.12	0.00
Comb.MF	*no short-sale*	0.15	0.11	0.07	0.06	0.05	0.02	0.00
	short-sale	0.34	0.27	0.23	0.20	0.18	0.09	0.00
	(margin = 0.5)	0.33	0.26	0.22	0.19	0.17	0.09	0.00
ATIC. Factor	*no short-sale*	0.12	0.12	0.11	0.06	0.05	0.02	0.00
	short-sale	0.20	0.17	0.16	0.14	0.11	0.04	0.00
	(margin = 0.5)	0.21	0.17	0.16	0.15	0.11	0.01	0.00
Comb.SV	*no short-sale*	0.05	0.08	0.09	0.08	0.07	0.05	0.00
	short-sale	0.13	0.14	0.18	0.19	0.17	0.11	0.00
	(margin = 0.5)	0.12	0.14	0.17	0.18	0.15	0.02	0.00
Comb.EGARCH	*no short-sale*	0.10	0.11	0.11	0.09	0.07	0.02	0.00
	short-sale	0.24	0.24	0.23	0.20	0.16	0.08	0.01
	(margin = 0.5)	0.20	0.20	0.21	0.19	0.15	0.07	0.01

Note: In no-short sale case, ▸ CER of the benchmark model fluctuates between 0.36 and 0.39 and converges to 0.37. In short-sale allowed case, CER of the benchmark model fluctuates between 0.17 and 0.26 and converges to 0.37.

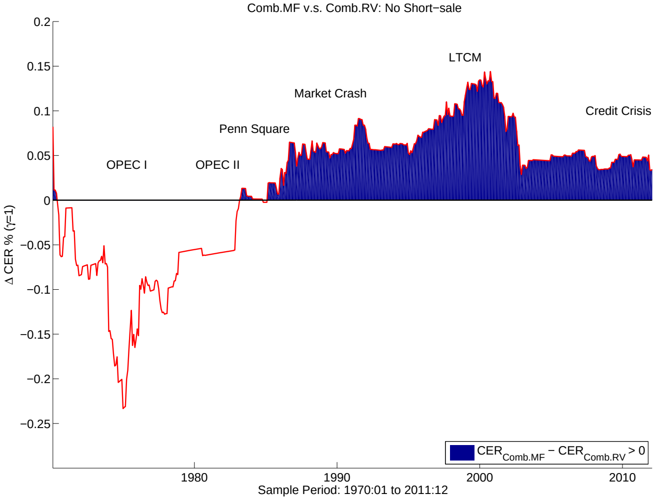
Comb.All vs. Comb.RV: no short-sale

Comb.All Obtains Higher CER than Comb.RV



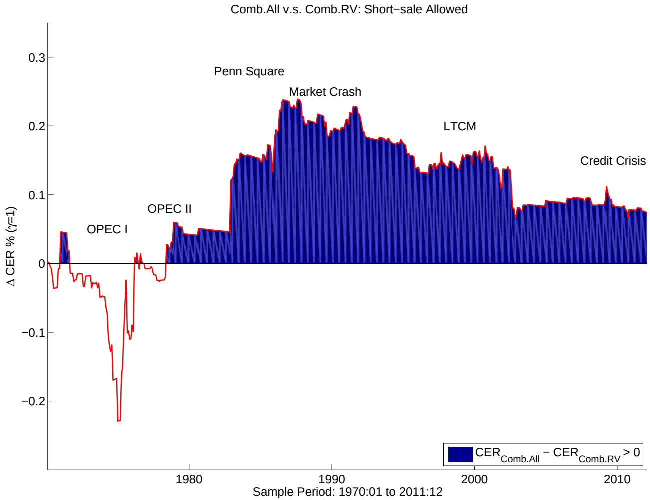
Comb.MF vs. Comb.RV: no short-sale

Comb.MF Obtains Higher CER than Comb.RV



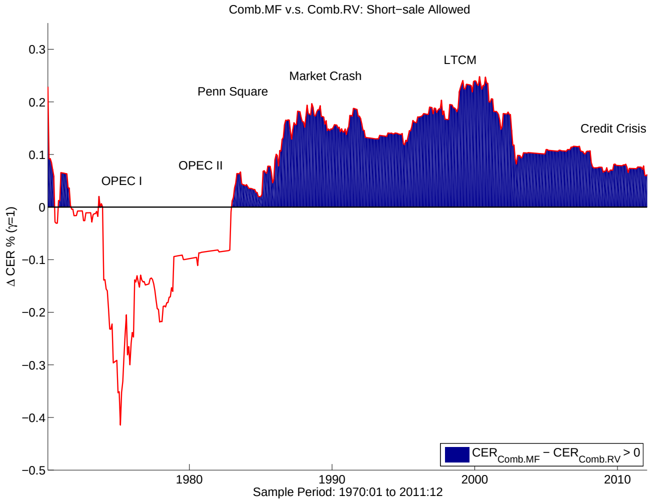
Comb.All vs. Comb.RV: short-sale allowed

Comb.All Obtains Higher CER than Comb.RV



Comb.MF vs. Comb.RV: short-sale allowed

Comb.MF Obtains Higher CER than Comb.RV



Why Macro-Finance Variables Help?

Compare density forecasts over ***A Particular Region of Interest***:

- The censored likelihood(csl) score function (Diks 2011):

$$S^{csl}(\hat{f}_t; y_{t+1}) = \underbrace{I(y_{t+1} \in A_{t+1}) \cdot \log \hat{f}_t(y_{t+1})}_{\text{A good forecast should have high density if } y_{t+1} \text{ falls in } A_{t+1},} + \underbrace{(1 - I(y_{t+1} \in A_{t+1})) \cdot \log\left(1 - \int_{A_{t+1}} \hat{f}_t(\mathbf{y}) d\mathbf{y}\right)}_{\text{and assign low probability to } A_{t+1} \text{ when } y_{t+1} \text{ not in } A_{t+1}}.$$

- The test statistic takes the same form as Amisano and Giacomini (2007) test above.

Comb.MF: Better on Right Tail

Table 2.c Diks 2011 Test Results

Sample Periods 1959 : 01 − 2011 : 12

	Upper 10% (Right Tail)				
Models	**Comb.RV**	**Comb.SV**	**Comb.EGARCH**	**Comb.MF**	**ATIC**
Comb.All	2.13	1.49	1.47	−1.62	0.83
Asy. p-value	(0.02*)	(0.07)	(0.07)	(0.95)	(0.20)
Models	**Comb.All**	**Comb.SV**	**Comb.EGARCH**	**Comb.MF**	**ATIC**
Comb.RV	−2.13	0.43	0.74	−1.92	0.07
Asy. p-value	(0.98)	(0.34)	(0.23)	(0.97)	(0.47)
Models	**Comb.All**	**Comb.RV**	**Comb.SV**	**Comb.EGARCH**	**ATIC**
Comb.MF	1.62	1.92	3.47	1.87	1.81
Asy. p-value	(0.05*)	(0.03*)	(0.00*)	(0.03*)	(0.04*)

Go to Left Tail

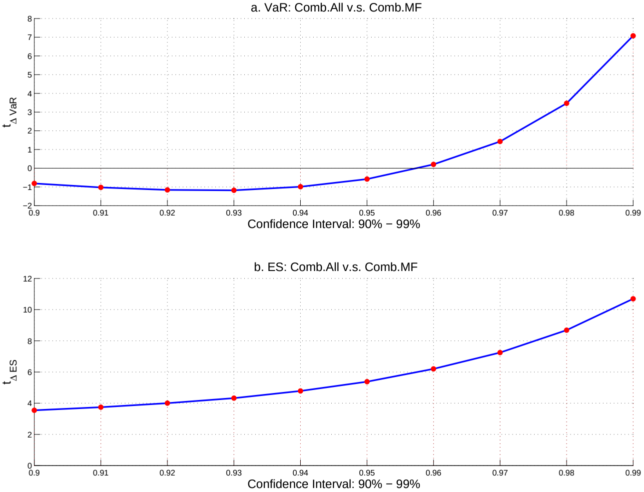
Measure the Market Risk

- ***Value at Risk (VaR)***: the cutoff point such that a loss will not happen with probability greater than p, say, $p = 90\% \ldots 99\%$.
- ***The Expected Shortfall (ES)***: the expected value of the worst $(1 - p)\%$ of returns.

The ES gives an idea of how bad the bad might be. VaR tells us nothing other than to expect a loss higher than VaR itself.

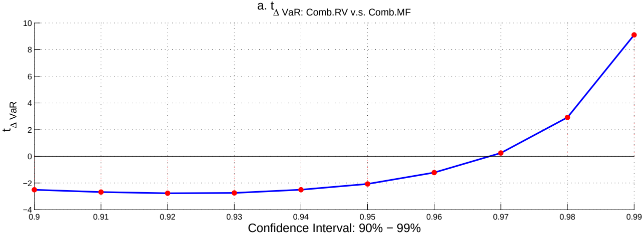
Risk Measure: Comb.All vs. Comb.MF

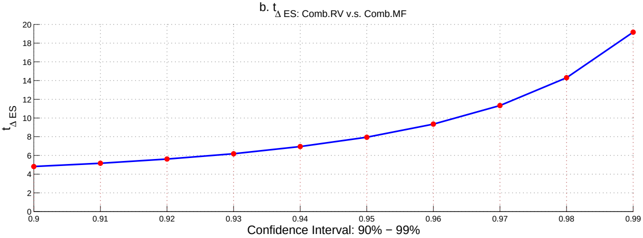
Risk Measure of Comb.All is Higher



Risk Measure: Comb.RV vs. Comb.MF

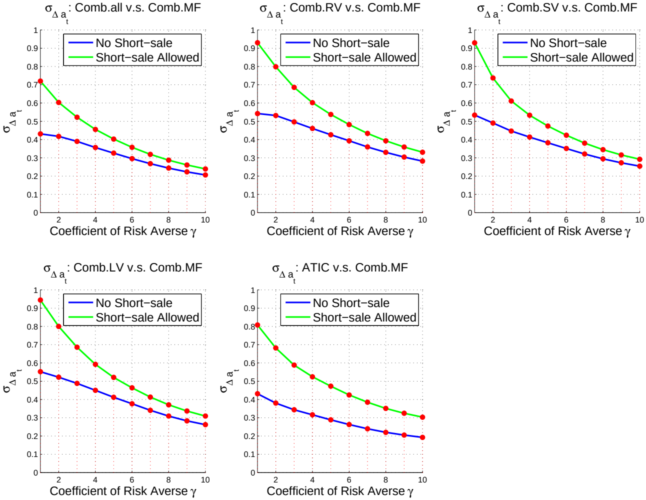
Risk Measure of Comb.RV is Higher





Impact of Risk Aversion

Portfolio Choice Converge as γ Increases



Conclusion

1. First, combined density forecast that uses various sources of information and assimilates multiple data generating processes performs the best.
2. Second, combining quantile density forecasts with macro-finance variables exhibit competitive density forecasting performance to volatility-based models.
3. Third, the proposed density forecasts yields a certainty equivalent return that is up to 0.35% per month higher than can be obtained with the combined forecasts that use EGARCH Student's-t.

Forecast Combination: An Illustration

- The optimal weight vector $\mathbf{w}_{t-1}^*$ is chosen to maximize:

$$f_{t-1}(\mathbf{w}_{t-1}) = \sum_{s=q+1}^{t-1} \log\Big[\sum_{m=1}^{M} w_{t-1,m} \cdot f(y_s|\mathbf{x}_{s-1}, \mathbf{y}_{s-1}, A_m)\Big].$$

  - *$f(y_s|\mathbf{x}_{s-1}, \mathbf{y}_{s-1}, A_m)$ is the predictive density of model A_m.*
  - *M is the number of models that are being combined.*
  - *$q = 120$ months: first in-sample periods.*
- $\mathbf{w}_{t-1}^* = (w_{t-1,1}^*, \ldots, w_{t-1,M}^*)'$ is a weight vector with nonnegative weights that sum to 1.

BACK TO GRAPH

Forecast Comparison: Difference-in-Likelihood Test

Amisano and Giacomini (2007) Test: Test Results

- Test statistic:

$$AG_{q,T} \equiv \frac{\Delta \overline{L}_t(y_{t+1})}{\hat{\sigma}/\sqrt{(T-q)}},$$

where

$$\begin{aligned}\Delta \overline{L}_t(y_{t+1}) &\equiv \frac{1}{T-q}\sum_{t=q+1}^{T} L_t(y_{t+1}) \\ &= \frac{1}{T-q}\sum_{t=q+1}^{T} \log f(y_{t+1}|\mathbf{x}_t,\mathbf{y}_t) - \log g(y_{t+1}|\mathbf{x}_t,\mathbf{y}_t).\end{aligned}$$

- The Null vs. The Alternative:

$$H_0 : E[\Delta L_t(y_{t+1})] = 0 \quad vs. \quad H_A : E[\Delta L_t(y_{t+1})] > 0.$$

Table.2.b Test Results: Combine All v.s. Individual Models

Sample Periods 1959 : 01 — 2011 : 12

Model Class	**Individual Density Forecasts**			
RVs	*RV-Gaussian* (1)	*RV-Gaussian* (2)	*RV-Student's t*	*RV-GED*
AG stat	1.66	1.60	3.69	2.22
Asy. p-value	(0.05*)	(0.06)	(0.00*)	(0.01*)
Boot. p-value	[0.01*]	[0.03*]	[0.00*]	[0.00*]
SVs	*Gaussian SV*	*Fat-tailed SV*	*Corr SV*	*Fat-tailed Corr SV*
AG stat	2.88	2.90	2.51	3.06
Asy. p-value	(0.00*)	(0.00*)	(0.01*)	(0.00*)
Boot. p-value	[0.02*]	[0.03*]	[0.00*]	[0.00*]
EGARCHs	*Gaussian* (1, 1)	*Gaussian* (1, 2)	*Gaussian* (2, 1)	*Gaussian* (2, 2)
AG stat	3.92	2.82	3.59	4.02
Asy. p-value	(0.00*)	(0.00*)	(0.00*)	(0.00*)
Boot. p-value	[0.00*]	[0.00*]	[0.00*]	[0.00*]
	Student-t (1, 1)	*Student-t* (2, 1)	*GED* (1, 1)	*GED* (2, 1)
AG stat	6.59	6.44	3.78	3.49
Asy. p-value	(0.00*)	(0.00*)	(0.00*)	(0.00*)
Boot. p-value	[0.00*]	[0.00*]	[0.00*]	[0.00*]
Combined MFs	*Dividend*	*Earnings*	*SVAR*	*Book to Mkt Ratio*
AG stat	3.43	3.57	1.85	2.26
Asy. p-value	(0.00*)	(0.00*)	(0.03*)	(0.01*)
Boot. p-value	[0.00*]	[0.00*]	[0.03*]	[0.01*]
	Net Equity Exp.	*Term Spread*	*Default Yield Spread*	*Inflation*
AG stat	2.34	2.27	1.87	2.14
Asy. p-value	(0.01*)	(0.01*)	(0.03*)	(0.02*)
Boot. p-value	[0.01*]	[0.01*]	[0.04*]	[0.00*]
	Unemployment Rate	*Industrial Production*	*Non-farm Payroll*	
AG stat	1.94	1.32	1.33	
Asy. p-value	(0.03*)	(0.09)	(0.09)	
Boot. p-value	[0.02*]	[0.09]	[0.08]	

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Comb.All: Better on Left Tail

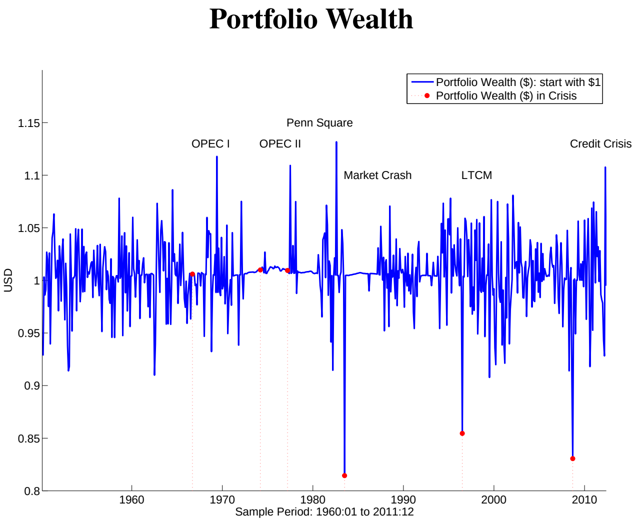
Table 2.c Diks 2011 Test Results

Sample Periods 1959 : 01 − 2011 : 12

	Lower 10% **(Left Tail)**				
Models	**Comb.RV**	**Comb.SV**	**Comb.EGARCH**	**Comb.MF**	**ATIC**
Comb.All	0.87	2.94	4.33	2.20	2.90
Asy. p-value	(0.19)	(0.00*)	(0.00*)	(0.01*)	(0.00*)
Models	**Comb.All**	**Comb.SV**	**Comb.EGARCH**	**Comb.MF**	**ATIC**
Comb.RV	−0.87	2.50	3.34	1.26	2.29
Asy. p-value	(0.19)	(0.01*)	(0.00*)	(0.10*)	(0.01*)
Models	**Comb.All**	**Comb.SV**	**Comb.EGARCH**	**Comb.MF**	**ATIC**
Comb.MF	−2.20	−1.26	1.27	1.91	1.89
Asy. p-value	(0.99)	(0.90)	(0.10)	(0.03)	(0.03)

Back to Right Tail

Portfolio Wealth Obtained by Comb.All



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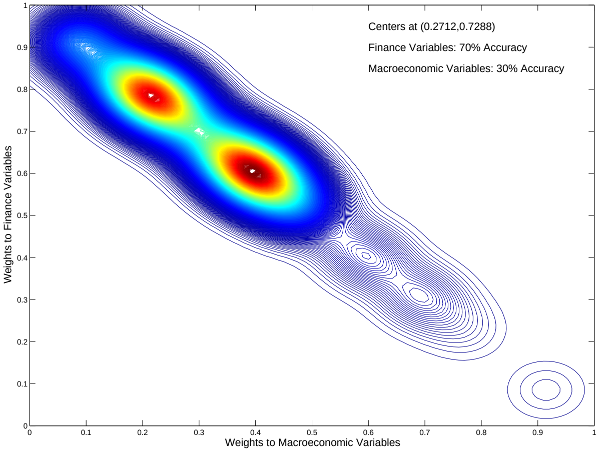
Predictive Accuracy Contribution

Comb.Macro: Macroeconomic Variables vs. Finance Variables



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Density Estimation in Portfolio Study

- By ***Density Transformation Theorem***, $f(R^e_{t+1}|\mathcal{F}_t)$ is estimated from:

$$f(R^e_{t+1}|\mathcal{F}_t) = \left|\frac{100}{R_{t+1}+1}\right| \cdot f(y_{t+1}|\mathbf{x}_t, \mathbf{y}_t, \mathbf{w}^*_t),$$

- because $y_{t+1} = 100 \cdot \log(R_{t+1}+1)$.

Optimal Portfolio Weight

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