Univariate Systemic Risk of Banking Industries in Developed Economies

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Abstract

This paper aims to study the forecasting performance of newly introduced "elicitable" ES-VaR models (Patton, Ziegel and Chen, 2019) for calculating the univariate systemic risk of banking industry indices. We choose two best performing ES-VaR models (Hybrid and GARCH-FZ) from Patton *et al*. (2019) to compare the forecasting performance with existing GARCH based models across a range of tail probability values (α). An out of sample forecast analysis of ES and VaR for five banking sector indices from large developed economies reveals that the GARCH-edf model performs the best during the global financial crisis period (2008-2009) while GARCH-FZ model ranks first during a recent period (2017-2018). We also find the best performing models can change across different developed banking industries and the size of tail probability values.

JEL classification: G01; G21; G28

Keywords: Risk management; ES; VaR; Backtesting; Financial crisis; Elicitability; Tails

1 Introduction

Many publications on the 2008 global financial crisis demonstrate that widespread failure of financial institutions has a spillover effect on the rest of the economy, requiring the adoption of a system-wide macroprudential approach to bank regulation (Borio, 2011). Therefore, the early-stage identification of systemic events in the banking sector is essential so that the regulators can effectively lower the probability of a systemic crisis or minimize its potential consequences by taking necessary measures (IMF, 2009).

The Basel Committee on Banking Supervision (BCBS) has adopted the Basel III regulations in response to the market failures exposed by the global 2007-2008 financial crisis (BCBS, 2010). New reforms have been added initiating from January 1st, 2019. Under these changes, the BCBS has, in part, substituted Value-at-Risk (VaR) by Expected Shortfall (ES) for calculating market risk capital requirements. Because VaR does not capture the conditionally expected losses adequately and lacks subadditivity while ES overcomes these shortcomings (Artzner, Delbaen, Eber and Heath, 1999).

Unlike expected shortfall, there is large literature on Value at Risk as it is a very popular and dominant (Dowd, 2005) measure of market risk (see Komunjer (2013) and McNeil *et al.* (2015)). Lack of empirical models for ES can be attributed to the fact that this measure is not “elicitable”. A risk measure is called “elicitable” if there exists a loss function such that the risk measure is the solution to minimizing the expected loss, which allows comparative backtesting and ranking of forecast models (Patton *et al.*, 2019). However, Fissler and Ziegel (2016) solves the problem of “elicitability’ and show that the VaR and ES can be elicited jointly. Recently, Patton *et al.* (2019) introduced new dynamic univariate models for ES and VaR using “FZ loss function” from Fissler and Ziegel (2016). Not surprisingly, there is also plenty of literature on evaluating and forecasting the systemic risk of banking sector using VaR models (De Jonghe, 2010; O'Brien and Szerszen, 2014; Xu *et al*., 2018, etc.). However, there is a dearth of existing literature on Expected Shortfall (ES) based systemic risk models applied for the banking sector.

This paper contributes to the literature by an extensive application of Patton *et al.* (2019) models and estimation methods in an out-of-sample analysis of forecasts of ES and VaR for five banking sector indices from large developed economies. We choose two best performing ES-VaR models (Hybrid and GARCH-FZ) from Patton *et al*. (2019) to compare the forecasting performance with existing GARCH based models across a range of tail probability values (α) popularly used in risk management. We find that ES-VaR models from Patton *et al.* (2019) outperform existing GARCH based models during the post-global financial crisis (GFC) period (2017-2018). However, GARCH-EDF, arguably the best existing model for ES (Engle and Manganelli (2004b), outperforms ES-VaR models from Patton *et al.* (2019) during the GFC period (2008-2009) contradicting results from Patton *et al.* (2019).

The rest of the paper is organized as follows. Section 2 discusses previous literature regarding ES and VaR models used in estimating and predicting the systemic risk of banking sector. Section 3 provides a brief description of the methodology and data collection process. In Section 4, we apply all the chosen models to daily return data of five banking sector indices and perform both in-sample and out of sample analysis. Finally, section 5 concludes. References, tables, graphs, and the supplemental appendix is provided afterward.

2 Previous Literature

Borri, Marianna, Giorgio and Sorrentino (2014) estimated systemic risk contributions of the Italian banking industry using ΔCoVar methodology first proposed by Adrian and Brunnermeier (2016) and measure banks' contribution to systemic risk by ΔCoVaR. Also, Xu *et* *al.* (2018) used the same methodology to measure systemic risk in the Chinese banking sector as this approach allows selecting banks that should be the focus of supervision even after the financial crash. In this paper, we choose the market return of industry indices to measure systemic risk instead of accounting variables because Borri *et al.* (2014) conclude that market-based variables are generally much stronger predictors of banks' share to systemic risk than balance sheet variables. They observe that measures of risk based on higher frequency market prices predict more accurate systemic risk as accounting rules provide enough degrees of freedom to make balance sheet less informative.

Fortin, Simonato, and Dionne (2018) investigates if a univariate or a multivariate modeling approach is more effective in forecasting the expected shortfall of stock portfolios. They find no significant differences between the systemic risk forecasting accuracy of univariate models and multivariate models with dynamic correlations. They also find that univariate models are more efficient and easier to employ than multivariate models. These findings are in line with our choice of univariate models while forecasting the systemic risk of the banking sector indices.

Researchers have captured systemic risks in the banking industry using many other methodologies too. For example, De Jonghe (2010) presents a market-based measure of European banks' systemic risk measured by the *Tail Beta*, that is, the probability of a steep decrease in a bank's stock price in case a banking industry index goes down. Also, Giglio (2010) evaluates the systemic default risk of large financial institutions by using information in bonds and CDS prices. Acharya, Pedersen, Philippon, and Richardson (2010) models a new systemic risk measure *SES* (systemic expected shortfall). *SES* is defined as the probability of a bank's undercapitalization in a future systemic event in which the whole financial system is also undercapitalized. Also, O'Brien and Szerszen (2014) study forecasting performance of VaR measures used by several large banks during and before the financial crisis. They find that variance decompositions by frequency of bank and benchmark VaR measures' show limited ability of the banks' VaR methodologies to adjust to the crisis-period market conditions.

3 Methodology and Data Collection

The limitation of VaR as a quantile measure is that the size of potential loss in measuring tail risk can not be calculated by VaR. Therefore, Expected Shortfall works as a supplement to VaR by providing the average return on a risky asset conditional on the return being below a given quantile of its VaR (Patton *et al.*, 2019). Mathematically, the tail probability (α) level VaR and ES estimated by,

$$ES_t = E[Y|Y_t \leq VAR_t, \mathcal{F}_{t-1}] \tag{1}$$

$$\text{Where } VaR_t = F_t^{-1}(\alpha), \text{ for } \alpha \in (0,1) \tag{2}$$

$$\text{And} \quad Y_t \,|\, \mathcal{F}_{t-1} \sim F_t \tag{3}$$

Here Yt is the return on an asset over a given time period with conditional (on the information set $\mathcal{F}_{t-1}$) distribution F_t, which we assume to be strictly increasing with finite mean.

There are plenty of models for VaR. However, the shortage of empirical models for expected shortfall can be attributed to historically less regulatory interest in ES as opposed to VaR. Lack of popularity for ES as a measure of systemic risk is mostly since ES is not "elicitable". According to Patton *et al.* (2019), a risk measure can be called elicitable if there exists a loss function such that the risk measure is the solution to minimizing the expected loss. Elicitability is crucial for systemic risk modeling as it facilitates comparative backtesting and ranking of forecast models. However, Fissler and Ziegel (2016) recently showed that the VaR and ES can be ES is jointly elicitable with VaR which facilitates designing new dynamic models for ES and VaR. Patton *et al.* uses the results from Fissler and Ziegel (2016) and build dynamic models for ES and VaR.

Patton *et al.* (2019) present four dynamic models for ES and VaR. All the models are semiparametric in the sense that they impose parametric structures for the dynamics of ES and VaR, but require no assumptions, beyond regularity conditions, on the conditional distribution of returns. Among those semiparametric models, GARCH-FZ is found to the best model for the lower tail probability (α) values while Hybrid model performs the best for higher tail probability (α) values. Therefore, we choose these two best performing models for ES and VaR from Patton *et al.* (2019) to estimate and forecast the systemic risk of banking industry.

Additionally, we test the other successful models from the volatility literature for ES and VaR (see Andersen *et al.*, 2006). These models are based on ARMA-GARCH dynamics for the conditional mean and variance and some assumptions for the distribution of the standardized residuals, with the ARMA model orders selected using the BIC. GARCH dynamics for the conditional mean and variance are the following:

$$Y_t = \mu_t + \sigma_t \eta_t$$

$$\eta_t \sim iid\ F_\eta\ (0, 1) \tag{4}$$

Following GARCH dynamics, VaR and ES are calculated as:

$$v_t = \mu_t + \mathbf{a}\sigma_t \ \ where\ a = F_\eta^{-1}\ (\boldsymbol{\alpha})$$

$$e^t = \mu_t + \boldsymbol{b}\sigma_t \ \ where\ b = E\ [\ \eta_t |\ \eta_t \leq a\ ] \tag{5}$$

where the standardized residual, η_t, is specified by two most common parametric choices for F_η within the existing VaR and ES literature:

$$\eta_t \sim iid\ N\ (0,1)$$

$$\eta_t \sim iid\ skew\ t\ (\ 0,\ 1,\ v,\ \lambda) \tag{6}$$

Finally, a non-parametric approach is also used to estimate the distribution of η_t using the empirical distribution function (EDF), which is arguably the best existing model (Engle and Manganelli, 2004b).

As discussed, we choose two semiparametric models from Patton *et al.* (2019). *The first* one is GARCH-FZ model which improves the fitted ARMA-GARCH model by estimating the parameters of that model via FZ loss minimization. Assume the following model for asset returns:

$$Y_t = \sigma_t \eta_t, \ \eta_t \sim iid\, F_\eta (0, 1) \tag{7}$$

$$\sigma^2 = \omega + \beta\, \sigma^2_{t-1} + \gamma Y^2_{t-1}$$

Here The conditional variance, σ^2, follows a GARCH (1,1) process. Then, VaR and ES are calculated as:

$$v_t = \alpha\sigma_t, \ where\ a = F^{-1}_{\eta} (\alpha)$$

$$e^t = b\sigma_t, \ where\ b = E\, [\, \eta_t \mid \eta_t \leq a] \tag{8}$$

Now we consider here estimating via FZ loss minimization (Fissler and Ziegel, 2016) instead of estimating the parameters of this model using (Q)MLE. This estimation approach is designed to produce the best fitting ES and VaR forecasts.

Second, a hybrid GAS / GARCH model is specified as:

$$Yt = \ \exp\{\, \kappa t\,\}\, \eta_t, \ \ \eta_t \sim iid\, F_\eta\, (0, 1)$$

$$\kappa_t = \omega + \beta\, \kappa_{t-1} + \gamma\ \ (1 / e_{t-1})\, (\, (1/\, \alpha)\, \mathbf{1}\, \{Y_{t-1} \ \leq v_{t-1}\, \}\, Y_{t-1} - e_{t-1}\,) + \delta \log |\, Y_{t-1} \tag{9}$$

The variable κ_t is the log-volatility and five parameters of this model (β, γ, δ, a, b) are estimated using Fissler and Ziegel (2016) or FZ loss minimization.

To summarize our choice of models for ES and VaR, two of the selected models, GARCH-N and GARCH-skt, are parametric (Andersen *et al.*, 2006), while GARCH-EDF (Engle and

Manganelli, 2004b) is non-parametric in nature. Finally, recently introduced Patton *et al.* (2019) semiparametric models are GARCH-FZ and Hybrid models.

This paper collects S&P Banks and FTSE 350 Banks, TOPIX (Tokyo) Banks, Euro Stoxx Banks and TSX Composite Banks indices to represent successively USA, UK, Japanese, European and Canadian banking industries. All the data are collected from Bloomberg terminal and All the tests are run in MATLAB. Patton *et al.* (2019) perform out of sample forecasting tests for a time horizon of 16 years (2000 to 2016). However, we estimate the chosen models using the first 27 years (1990-2016) data as our in-sample period, retain those parameter estimates throughout the out of sample (OOS) period and perform OOS evaluation and model comparison analysis using recent OOS period (2017-2018). To check out the robustness of the forecasting performance, we estimate the same models using the first 10 years (1990-1999) as our in-sample period and perform OOS forecasting tests for the global financial crisis (GFC) period of 2 years (2008-2009). We perform additional forecasting tests during the GFC period as an important characteristic of a good systemic risk exposure model is that it is functional across crises (Sedunov, 2016). Furthermore, this paper compares all the chosen models across a range of tail probability (α) values (e.g.; 0.01, 0.025, 0.05, 0.075, 0.10) which are common in risk management practices. As a ranking mechanism, this paper uses Diebold and Mariano (1995) tests to identify the best-performing models for ES and VaR. Additionally, we execute simple regression-based goodness of fit tests, related to those of Engle and Manganelli (2004a) to backtest the ES forecasts.

4 Results and Discussions

Table 1 shows summary statistics on the return series of the chosen five banking sector indices. Average annualized returns range from 1.1% for the TOPIX Banks index to 12.46% for the TSX Banks index, and annualized standard deviations range from 30.92% to 19.31%. All return series exhibit mild positive skewness except S&P Banks showing moderate positive skewness (0.809). All return series show substantial kurtosis highest being 26 for S&P banks and lowest being 7.9 for TOPIX banks. The sample VaR and ES for four choices of alpha are also shown in table 1 where ES and VaR values associated with the lowest alpha show lowest values as usual.

[INSERT THE TABLE 1 HERE]

Table 2 shows findings from standard time series models estimated on return series based on the banking industry indices over the in-sample period (Jan 1990 to Dec 2018). In the upper panel, we present the estimated ARMA and GARCH (1,1) model parameters. Then the lower panel presents the estimated parameters the skew t distribution fitted to the standardized residuals. All these parameters conform to the values obtained by Patton et al. (2019) and other papers showing similar time-series data.

[INSERT THE TABLE 2 HERE]

Now table 3 demonstrates present estimates of the parameters of the models presented in the methodology part. We also report standard errors in brackets. The parameter estimates for the S&P 500 index only for $\alpha = 0.05$ are reported. We observe that the persistence of GARCH processes is high and the model-implied average values of VaR and ES are similar to the sample values at $\alpha = 0.05$ reported in Table 1. We can observe that the hybrid model fits slightly better than the GARCH-FZ model across different banking industry indices as the average loss is slightly lower in all cases. Also, the GARCH forcing variable **(δ)** is large and significantly different from zero.

[INSERT THE TABLE 3 HERE]

The tables 4 (a,b,c) present the average OOS losses, using the FZ0 loss function for each of the five models, for the five bank industry return series. The lowest values in each column are highlighted in bold, and the second-lowest are in italics. We observe that the best performing models for the selected bank industry returns are different depending on the chosen periods. Also, tables 4 (a,b,c) presents the p-values from the tests of the goodness-of-fit of the VaR and ES forecasts. Entries greater than 0.10 (indicating no evidence against optimality at the 0.10 level) mean that the model passes goodness of fit tests. For example, for US banks, only GARCH-skt model passes optimality tests.

[INSERT THE TABLE 4 (a,b,c) HERE]

While average losses are useful for an initial look at average loss forecast performance, we can not say if the models are performing significantly better . Tables 5 presents Diebold-Mariano t-statistics on the loss differences, for the 5 selected bank industry indices for the recent time period (2017-2018). Corresponding tables for the other tail probability values (α) are presented in the supplemental appendix. The tests are conducted as a "row model minus column model". So, a positive number indicates that the column model outperforms the row model.

Tables 6.a to 6.e ranks the models based on the performance according to Diebold-Mariano t-statistics on the loss differences. We can conclude from tables 6.1 to 6.e that GARCH-FZ, a semiparametric model, outperforms other models for the recent OOS period (2016-2018). Findings from this time period differ to some extent that GARCH-FZ model is the best performing model for forecasting banking industry systemic risk, while Patton et al. (2019) concluded Hybrid model to be the overall best performing model.

[INSERT TABLE 5 HERE]

[INSERT TABLES 6.a to 6.e HERE]

However, the results are significantly different for another OOS period, that is, the GFC period (2008-2009). According to table 7.a to 7.e, GARCH-edf, a non-parametric model, outperforms the other models across different tail probability values (α) except when α = 0.10. GARCH-N model seems to outperform all other models during GFC period. These findings largely contradict with Patton *et at.* (2019) which found that semiparametric VAR and ES models outperform non-parametric models. The observation that the best performing models can change based on how deep the tails we are remains the same. Interestingly, the ranking of the best performing models can also drastically be different based on the banking industry indices of different international economies. Therefore, size of tail probability values and differences of banking industries can be considered significant determinants of best performing systemic risk models.

[INSERT TABLES 7.a to 7.e HERE]

5 Conclusion

The widespread failure of financial institutions during the 2008 global financial crisis has placed unique emphasis on estimating and forecasting systemic riks of banking industries around the world. Moreover, the Basel Committee on Banking Supervision (BCBS) has adopted the Basel III regulations partially substituting Value-at-Risk (VaR) by Expected Shortfall (ES) for calculating market risk capital requirements. This paper attempts to fill the research gap evaluating and forecasting systemic risk of different banking industries utilizing recently introduced ES-VaR models (Patton *et al.*, 2019). A large number of extensive applications of popular and newly introduced ES-VaR models reveal that the GARCH-edf model performs the best during the global financial crisis period (2008-2009) while GARCH-FZ model ranks first during a recent period

(2017-2018). We also find the best performing models can change across different developed banking industries and the size of tail probability values. Future researchers may attempt to apply these models in other markets such as options markets or industries such as the insurance industry. Also, the derivation of multivariate models keeping the main contribution of "elicitability" in ES models can be an interesting extension in this field.

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Table 1: Summary Statistics of All the Indices

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks
Mean	11.999	10.407	6.086	12.459	1.109
StdDev	30.928	26.378	26.49	19.311	29.537
Skew	0.809	0.373	0.202	0.341	0.387
Kurt	26.004	14.046	13.066	13.1	7.993
VaR-0.01	-5.099	-4.413	-5.01	-3.253	-4.918
VaR-0.025	-3.539	-3.186	-3.406	-2.372	-3.619
VaR-0.05	-2.576	-2.365	-2.511	-1.766	-2.77
VaR-0.10	-1.689	-1.67	-1.69	-1.237	-1.989
ES-0.01	-7.863	-6.169	-6.571	-4.461	-6.45
ES-0.025	-5.665	-4.691	-5.049	-3.431	-5.055
ES-0.05	-4.341	-3.704	-3.987	-2.735	-4.098
ES-0.10	-3.202	-2.838	-3.014	-2.096	-3.216

Table 2: ARMA, GARCH, and Skew t results

Parameters	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks
Φ_0	0.0502	0.0453	0.0296	0.0527	0.0062
ω	0.0173	0.0147	0.0197	0.0126	0.0728
β	0.9101	0.909	0.897	0.8921	0.847
γ	0.0856	0.0896	0.0983	0.1017	0.1426
ν	7.3604	8.5473	6.945	8.3869	6.3845
λ	0.0148	0.0115	-0.0575	0.0082	0.0796

Table 3: Estimated parameters of GAS models for VaR and ES

	S&P Banks		FTSE Banks		EURO Banks		TSX Banks		TOPIX Banks	
Parameters	**GARCH-FZ**	**HYBRID**	**GARCH-FZ**	**HYBRID**	**GARCH-FZ**	**HYBRID**	**GARCH-FZ**	**HYBRID**	**GARCH-FZ**	**HYBRID**
β	0.8886	0.9644	0.9084	0.9809	0.8944	0.9675	0.891	0.9632	0.8816	1.2531
(s.e.)	0.0399	0.0057	0.0354	0.0024	0.0612	0.0022	0.0338	0.0042	0.0501	0.0093
γ	0.0523	0.0134	0.0518	0.0112	0.1491	0.0107	0.086	0.0095	0.1628	0.0128
(s.e.)	0.004	0.0015	0.0065	0.001	0.025	0.0008	0.0114	0.0016	0.0257	0.0012
δ		0.0215		0.0088		0.0246		0.0233		0.0367
(s.e.)		0.0042		0.0007		0.0016		0.0017		0.005
a	-2.2165	-2.6223	-2.0209	-2.5476	-1.3958	-3.0148	-1.7753	-2.3818	-1.2983	-2.8528
(s.e.)	0.1455	2.0865	0.1254	2.6357	0.0752	1.4954	0.1378	1.9504	0.1816	0.977
b	-3.0153	-3.6812	-2.7581	-3.4708	-1.9047	-4.1093	-2.3348	-3.331	-1.7335	-3.8466
(s.e.)	0.2942	2.9338	0.25	3.5932	0.2346	2.0438	0.2386	2.7138	0.3091	1.3143
Avg. Loss	1.1059	1.0759	1.0988	1.078	1.0613	1.0406	0.7736	0.753	1.2531	1.2252

After the Global Financial Crisis (2017-2018)

Table 4.a: Average Losses and Goodness of Fit Tests (Alpha = 0.05)

	Avg loss (S&P Banks)	**MZ-VaR**	**MZ-ES**	**Avg loss (FTSE Banks)**	**MZ-VaR**	**MZ-ES**
GCH-n	*1.149*	0.207	0.083	*1.076*	0.009	0.021
GCH-skt	**1.148**	**0.101**	0.045	**1.075**	0.026	0.021
GCH-edf	*1.149*	0.032	0.029	1.077	0.014	0.014
GCH-FZ	1.155	0.031	0.013	1.1	0	0
Hybrid	1.162	0	0	1.091	0	0

Table 4.b: Average Losses and Goodness of Fit Tests (Alpha = 0.05)

	Avg loss (Euro Banks)	**MZ-VaR**	**MZ-ES**	**Avg loss (TSX Banks)**	**MZ-VaR**	**MZ-ES**
GCH-n	1.26	0	0	*0.685*	0	0
GCH-skt	1.25	0	0	0.686	0	0
GCH-edf	1.256	0	0	**0.684**	0	0
GCH-FZ	**1.242**	0	0	0.686	0	0
Hybrid	*1.248*	0	0	0.694	0	0

Table 4.c: Average Losses and Goodness of Fit Tests (Alpha = 0.05)

Avg loss	**(TOPIX)**	**MZ-VaR**	**MZ-ES**
GCH-n	1.271	0.076	0.042
GCH-skt	1.274	0.006	0.013
GCH-edf	1.27	0.183	0.058
GCH-FZ	1.27	0.173	0.132
Hybrid	1.256	0.229	0.249

Table 5: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, S&P Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		0.777	0.174	-1.09	-1.055
GCH-skt	-0.777		-1.108	-1.408	-1.19
GCH-edf	-0.174	1.108		-1.266	-1.129
GCH-FZ	1.09	1.408	1.266		-0.585
Hybrid	1.055	1.19	1.129	0.585	

Table 6.a Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.01)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	5	3	5	5	1	3.8
G-Skt	3	1	3	1	4	**2.4**
G-EDF	2	2	4	3	2	2.6
G-FZ	1	4	2	2	3	**2.4**
Hybrid	4	5	1	4	5	3.8

Table 6.b Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.025)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	5	4	5	5	3	4.4
G-Skt	4	2	2	3	2	2.6
G-EDF	3	1	1	2	4	2.2
G-FZ	2	3	3	1	1	**2**
Hybrid	1	5	4	4	5	3.8

Table 6.c Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.05)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	5	4	4	4	4	4.2
G-Skt	4	2	2	3	1	**2.4**
G-EDF	3	3	3	1	3	2.6
G-FZ	2	1	5	2	2	**2.4**
Hybrid	1	5	1	5	5	3.4

Table 6.d Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.075)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	5	3	4	4	5	4.2
G-Skt	4	4	2	1	2	2.6
G-EDF	3	5	3	3	3	3.4
G-FZ	2	1	5	2	1	**2.2**
Hybrid	1	2	1	5	4	2.6

Table 6.e Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.1)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	5	5	2	5	5	4.4
G-Skt	4	3	4	2	2	3
G-EDF	3	4	3	3	3	3.2
G-FZ	2	2	5	1	1	**2.2**
Hybrid	1	1	1	4	4	**2.2**

During GFC (2008-2009)

Table 7.a : Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.01)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	4	5	3	4	1	3.4
G-Skt	2	2	1	2	4	2.2
G-EDF	1	1	2	3	3	**2**
G-FZ	3	4	4	1	2	2.8
Hybrid	5	3	5	5	5	4.6

Table 7.b Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.025)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	4	5	4	4	2	3.8
G-Skt	2	3	1	3	4	2.6
G-EDF	1	1	2	2	3	**1.8**
G-FZ	3	2	3	1	1	2
Hybrid	5	4	5	5	5	4.8

Table 7. c Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.05)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	3	3	4	1	2	2.6
G-Skt	2	2	2	5	4	3
G-EDF	1	1	3	2	3	**2**
G-FZ	4	4	1	4	1	2.8
Hybrid	5	5	5	3	5	4.6

Table 7.d Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.075)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	1	4	4	1	2	**2.4**
G-Skt	3	3	2	4	5	3.4
G-EDF	2	1	3	3	3	**2.4**
G-FZ	4	2	1	5	1	2.6

Hybrid	5	5	5	2	4	4.2

Table 7.e Ranking of Performance of different models based on Diebold-Mariano t-statistics (Alpha = 0.1)

	S&P Banks	FTSE Banks	Euro Banks	TSX Banks	TOPIX Banks	AVG
G-N	2	4	2	2	1	**2.2**
G-Skt	4	2	4	4	3	3.4
G-EDF	3	1	3	3	2	*2.4*
G-FZ	1	3	1	5	4	2.8
Hybrid	5	5	5	1	5	4.2

Figure 1

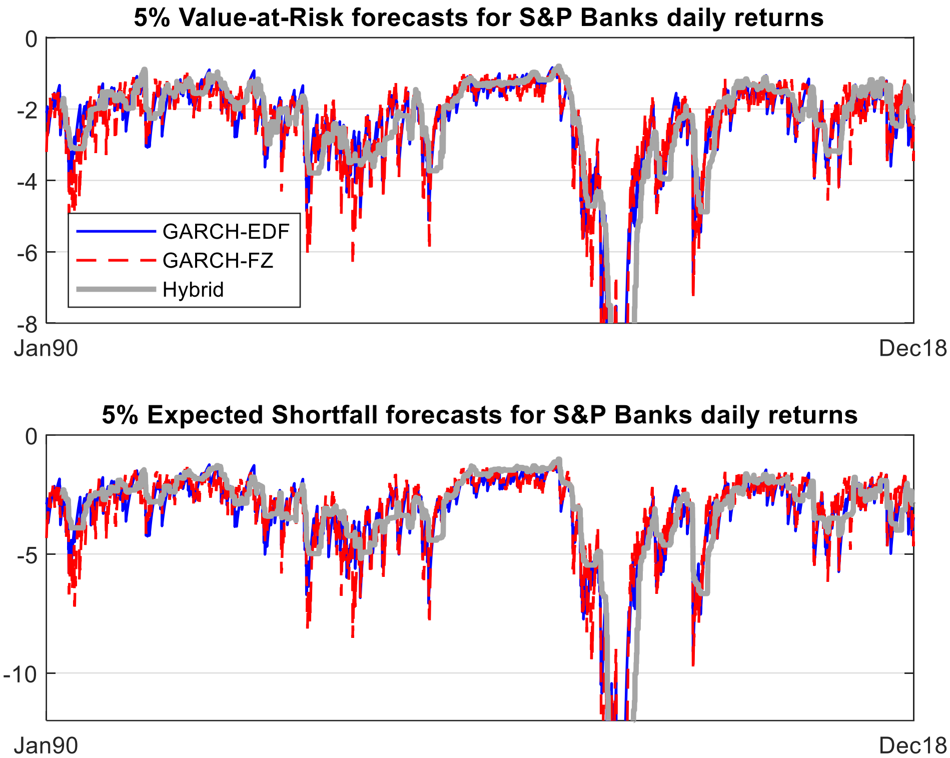
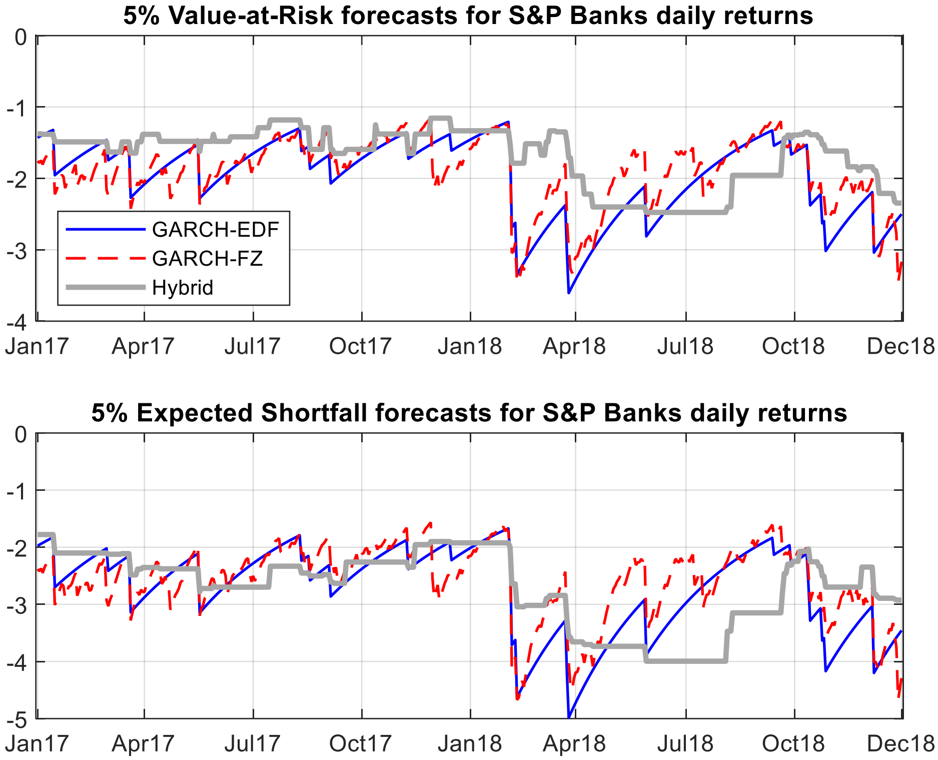

5% Value-at-Risk forecasts for S&P Banks daily returns
0
-2
-4
-6
-8
Jan90
Dec18
GARCH-EDF
GARCH-FZ
Hybrid
5% Expected Shortfall forecasts for S&P Banks daily returns
0
-5
-10
Jan90
Dec18

Figure 2



5% Value-at-Risk forecasts for S&P Banks daily returns
0
-1
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-3
-4
Jan17
Apr17
Jul17
Oct17
Jan18
Apr18
Jul18
Oct18
Dec18
GARCH-EDF
GARCH-FZ
Hybrid
5% Expected Shortfall forecasts for S&P Banks daily returns
0
-1
-2
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-4
-5
Jan17
Apr17
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Jan18
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Jul18
Oct18
Dec18

Supplemental Appendix

Recent Period (2017-2018)

Table S1: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, Euro Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		3.975	2.254	3.126	0.913
GCH-skt	-3.975		-5.723	1.835	0.148
GCH-edf	-2.254	5.723		2.699	0.586
GCH-FZ	-3.126	-1.835	-2.699		-0.513
Hybrid	-0.913	-0.148	-0.586	0.513	

Table S2: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, FTSE Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		0.938	-0.43	-2.618	-1.476
GCH-skt	-0.938		-1.463	-2.904	-1.619
GCH-edf	0.43	1.463		-2.722	-1.342
GCH-FZ	2.618	2.904	2.722		0.806
Hybrid	-1.476	1.619	1.342	-0.806	

Table S3: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, TSX Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		-0.153	0.344	-0.106	-1.071
GCH-skt	0.153		1.174	0.198	-1.005
GCH-edf	-0.344	-1.174		-1.634	-1.223
GCH-FZ	0.106	-0.198	1.634		-1.051
Hybrid	1.071	1.005	1.223	1.051	

Table S4: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, TOPIX Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		-0.629	1.753	0.494	1.356
GCH-skt	0.629		1.264	1.149	1.604
GCH-edf	-1.753	-1.264		-0.175	1.237

GCH-FZ	-0.494	-1.149	0.175		1.281
Hybrid	-1.356	-1.604	-1.237	-1.281	

During GFC (2008-2009)

Table S5: Average Losses and Goodness of Fit Tests (Alpha = 0.05), Euro Banks

	Avg loss	MZ-VaR	MZ-ES
GCH-n	1.716	0.006	0.005
GCH-skt	1.693	0.006	0.011
GCH-edf	1.695	0.007	0.012
GCH-FZ	1.693	0.002	0.005
Hybrid	1.706	0.001	0.001

Table S6: Average Losses and Goodness of Fit Tests (Alpha = 0.05), FTSE Banks

	Avg loss	MZ-VaR	MZ-ES
GCH-n	1.768	0.064	0.038
GCH-skt	1.765	0.139	0.079
GCH-edf	1.764	0.139	0.085
GCH-FZ	1.783	0.038	0.016
Hybrid	1.839	0	0

Table S7: Average Losses and Goodness of Fit Tests (Alpha = 0.05), TOPIX Banks

	Avg loss	MZ-VaR	MZ-ES
GCH-n	1.605	0.455	0.29
GCH-skt	1.619	0.095	0.095
GCH-edf	1.609	0.334	0.258
GCH-FZ	1.594	0.382	0.328
Hybrid	1.652	0.073	0.005

Table S8: Average Losses and Goodness of Fit Tests (Alpha = 0.05), S&P Banks

	Avg loss	MZ-VaR	MZ-ES
GCH-n	1.787	0.163	0.137
GCH-skt	1.788	0.122	0.13
GCH-edf	1.783	0.163	0.17
GCH-FZ	1.796	0.037	0.039
Hybrid	1.809	0.002	0

Table S9: Average Losses and Goodness of Fit Tests (Alpha = 0.05), TSX Banks

	Avg loss	MZ-VaR	MZ-ES
GCH-n	1.787	0.163	0.137
GCH-skt	1.788	0.122	0.13
GCH-edf	1.783	0.163	0.17
GCH-FZ	1.796	0.037	0.039
Hybrid	1.809	0.002	0

Table S10: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, Euro Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		2.668	2.638	1.336	0.231
GCH-skt	-2.668		-2.778	0.011	-0.344
GCH-edf	-2.638	2.778		0.211	-0.282
GCH-FZ	-1.336	-0.011	-0.211		-0.381
Hybrid	-0.231	0.344	0.282	0.381	

Table S11: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, FTSE Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		1.401	1.204	-1.266	-1.544
GCH-skt	-1.401		0.625	-1.574	-1.629
GCH-edf	-1.204	-0.625		-1.62	-1.645
GCH-FZ	1.266	1.574	1.62		-1.401
Hybrid	1.544	1.629	1.645	1.401	

Table S12: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, TOPIX Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		-1.665	-1.228	1.813	-1.196
GCH-skt	1.665		1.87	2.689	-0.851
GCH-edf	1.228	-1.87		2.388	-1.118
GCH-FZ	-1.813	-2.689	-2.388		-1.452
Hybrid	1.196	0.851	1.118	1.452	

Table S13: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05, S&P Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		0.397	1.522	-0.741	-0.725
GCH-skt	0.397		1.64	-0.712	-0.706
GCH-edf	-1.522	-1.64		-1.006	-0.858
GCH-FZ	0.741	0.712	1.006		-0.506
Hybrid	0.725	0.706	0.858	0.506	

Table S14: Diebold-Mariano t-statistics on average out-of-sample loss differences Alpha = .05,TSX Banks

	GCH-n	GCH-skt	GCH-edf	GCH-FZ	Hybrid
GCH-n		-1.823	-1.218	-1.19	-0.306
GCH-skt	1.823		2.202	0.773	0.167
GCH-edf	1.218	-2.202		-0.497	-0.166
GCH-FZ	1.19	-0.773	0.497		-0.061
Hybrid	0.306	-0.167	0.166	0.061	