Forecasting stock price volatility: New evidence from the GARCH-MIDAS model

Lu Wanga, Feng Ma, Jing Liu, Lin Yang

Presenter: Afet Ibadova

Agenda

1. Hypothesis
2. Model Contributions
3. Data and Methodology
4. GARCH-MIDAS Model Extensions
5. Estimation Results
6. Conclusion

Hypothesis

Main Hypothesis: Incorporating asymmetry and extreme volatility effects into the GARCH-MIDAS model significantly improves its ability to forecast stock price volatility

Key points:

- **Asymmetry Effect**: This concept highlights that stock returns react differently to positive and negative news
- **Extreme Volatility Effect**: Extreme events, such as financial crises or sudden economic shifts, cause abnormal volatility. These events can be identified and adjusted for within the model to enhance its forecasting accuracy.

Model Contributions

The extended model accounts for:

(a) the influence of extreme events on the stock volatilities of small and large news,

(b) the asymmetric responses of the stock return volatility to good versus bad news,

(c) the predictive accuracy of our extended volatility models.

Context and Contributions:

- **Impact of Major Changes:** Factors like extreme weather events, political disputes, and economic policies alter volatility.
- **Volatility Thresholds:** Adoption of thresholds for extreme returns enhances modeling and forecasting.
- **New Perspectives:** New models constructed to improve predictability and forecasting accuracy.

Data and Methodology

- **Data Source**:
    - Daily S&P 500 index data from 1991 to 2016.
    - In-sample: January 1991 to January 2006
    - Out-of-sample: February 2006 to December 2016
- **Evaluation**:
    - In-sample and out-of-sample performance.
    - Comparison using various loss functions (MSE, MAE, HMSE, HMAE, QLIKE).
- **Objective**:
    - Test the effectiveness of the extended GARCH-MIDAS models.

GARCH-MIDAS Model Overview

- **Components**:
  - Short-term (high-frequency) volatility.
  - Long-term (low-frequency) volatility.
- **Decomposition**:
  - The model separates daily fluctuations from longer-term trends.
- **Advantages**:
  - More accurate representation of volatility dynamics.
  - Better forecasting performance.

Table 1
The typology of GARCH-MIDAS and its extensions.

Model number	Asymmetry effect in short-term	Asymmetry effect in long-term	Extreme volatility effect in short-term	Extreme volatility effect in long-term	Model description
Model 0					The basic GARCH-MIDAS model
Model 1	✓				Including asymmetry in short-term volatility
Model 2		✓			Including asymmetry in long-term volatility
Model 3			✓		Including threshold in short-term volatility
Model 4				✓	Including threshold in long-term volatility
Model 5	✓		✓		Including asymmetry and threshold in short-term volatility
Model 6		✓		✓	Including asymmetry and threshold in long-term volatility
Model 7	✓	✓			Including asymmetry in both short- and long-term volatility
Model 8	✓			✓	Including asymmetry in short-term volatility and threshold in long-term volatility
Model 9	✓	✓		✓	Including asymmetry in both short- and long-term volatility and extreme in long-term volatility
Model 10			✓	✓	Including extreme in both short- and long-term volatility
Model 11		✓	✓		Including asymmetry in long-term volatility and extreme in short-term volatility
Model 12		✓	✓	✓	Including asymmetry in long-term volatility and extreme in both short- and long-term volatility
Model 13	✓	✓	✓		Including asymmetry in both short- and long-term volatility and extreme in short-term volatility
Model 14	✓		✓	✓	Including asymmetry in short-term volatility and extreme in both short- and long-term volatility
Model 15	✓	✓	✓	✓	Including asymmetry and extreme in both short- and long-term volatility

Estimation results

- Most parameters are statistically significant (indicated by ***).
- Models with asymmetry (γ) show bad news has a greater short-term impact.
- Negative extreme shocks (θ−) have a significant effect on volatility.
- Models incorporating both asymmetry and extreme volatility effects perform best.

Table 2
Estimation results of GARCH-MIDAS and its extensions.

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
μ	0.056***	0.025***	0.055***	0.041***	0.056***	0.020**	0.056***	0.026***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.009)	(0.010)	(0.009)
α	0.102***	0.001	0.101***	0.099***	0.099***	0.065	0.097***	0.001
	(0.006)	(0.016)	(0.009)	(0.000)	(0.008)	(0.072)	(0.010)	(0.014)
β	0.851***	0.840***	0.847***	0.869***	0.857***	0.848***	0.852***	0.851***
	(0.011)	(0.009)	(0.018)	(0.012)	(0.016)	(0.011)	(0.018)	(0.029)
ω	6.483***	7.4013***	7.223***	8.151***	6.717***	10.121***	6.227***	7.153***
	(1.670)	(1.439)	(2.079)	(1.670)	(2.034)	(1.832)	(1.819)	(1.769)
m	0.614***	0.340***	0.381***	0.536***	0.721***	0.384***	−0.192	0.321***
	(0.041)	(0.051)	(0.070)	(0.064)	(0.049)	(0.066)	(0.233)	(0.055)
θ	0.166***	0.027***		0.208***		0.186***		
	(0.008)	(0.002)		(0.033)		(0.012)		
θ^*					0.296***			
					(0.077)			
θ^+			0.006				0.025	−0.007
			(0.017)				(0.059)	(0.022)
θ^-			0.049***				0.227***	0.062***
			(0.016)				(0.085)	(0.021)
θ^{+*}					−0.001		−0.011	
					(0.478)		(0.019)	
θ^{-*}					0.234***		0.059*	
					(0.017)		(0.017)	
γ		0.199***						0.195***
		(0.015)						(0.022)
γ^+						−0.097*		
						(0.071)		
γ^-						0.211***		
						(0.072)		
γ^{+*}				−0.129***		0.047***		
				(0.017)		(0.016)		
γ^{-*}				0.066***		−0.096***		
				(0.019)		(0.012)		

Estimation results

- Parameters μ, α, β, and ω are statistically significant in most models.
- Negative shocks (θ−) have a significant impact on volatility in many models.
- Asymmetry parameters (γ, γ+, γ−) show the differential impact of news.
- Models with combined effects of asymmetry and extreme volatility perform better.

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
μ	0.077^{***}	0.027^{***}	0.041^{**}	0.033^{***}	0.041^{***}	0.020^{***}	0.019^{**}	0.017^{***}
	(0.010)	(0.010)	(0.001)	(0.011)	(0.010)	(0.005)	(0.010)	(0.003)
α	0.101^{***}	0.001	0.096^{***}	0.050^{***}	0.095^{***}	0.070^{***}	0.002	0.002
	(0.009)	(0.015)	(0.017)	(0.014)	(0.016)	(0.040)	(0.015)	(0.013)
β	0.834^{***}	0.849^{***}	0.877^{***}	0.889^{***}	0.882^{***}	0.859^{***}	0.839^{***}	0.870^{***}
	(0.015)	(0.027)	(0.015)	(0.010)	(0.011)	(0.031)	(0.015)	(0.038)
ω	5.792^{***}	6.906^{***}	7.633^{***}	7.606^{***}	7.478^{***}	9.377^{***}	11.677^{***}	8.046^{***}
	(2.193)	(1.500)	(1.721)	(1.478)	(1.472)	(1.621)	(2.650)	(1.467)
m	0.699^{***}	−0.020	0.711^{***}	-0.495^{***}	0.521^{***}	0.618^{***}	−0.020	−0.031
	(0.040)		(0.065)	(0.035)	(0.076)	(0.102)		(0.212)
θ								
θ^*	0.252^{***}		0.198^{***}				0.199^{***}	
	(0.068)		(0.030)				(0.019)	
θ^+		0.003		-0.215^{***}	-0.308^{***}	-0.093^{**}		0.011
		(0.021)		(0.021)	(0.062)	(0.039)		(0.019)
θ^-		−0.057		0.001	0.001	0.251^{***}		0.323^{***}
		(0.045)		(0.113)	(0.182)	(0.032)		(0.089)
θ^{+*}	−0.001	0.049^{**}	0.177^{***}		−0.000017		-0.106^{**}	0.063^{***}
	(0.120)	(0.021)	(0.048)		(0.148)		(0.051)	(0.023)
θ^{-*}	0.248^{***}	0.219^{***}	0.127^{**}		−0.000011		0.204^{***}	0.106^{**}
	(0.017)	(0.062)	(0.071)		(0.283)		(0.030)	(0.056)
γ	0.121^{***}	0.1925^{***}						
	(0.017)	(0.020)						
γ^+						-0.134^{***}	-0.083^{***}	−0.086
						(0.028)	(0.010)	(0.026)
γ^-						0.193^{***}	0.222^{***}	0.278^{***}
						(0.039)	(0.023)	(0.032)
γ^{+*}			-0.091^{***}	-0.081^{***}	-0.125^{***}	0.038^{*}	-0.027^{**}	0.059^{***}
			(0.014)	(0.015)	(0.016)	(0.026)	(0.018)	(0.015)
γ^{-*}			0.096^{***}	0.106^{***}	0.067^{***}	-0.084^{***}	-0.118^{***}	-0.112^{***}
			(0.018)	(0.019)	(0.018)	(0.027)	(0.033)	(0.021)

Estimation Results

- Models 12, 14, and 15 perform best based on the result of loss functions.
- Model 15 shows superior performance across multiple loss functions.
- Enhanced models generate better forecasts than the benchmark model.

Implications:

- Incorporating asymmetry and extreme volatility effects improves predictive accuracy.
- Better performance in real-world forecasting scenarios.

Table 3
The MCS test results for the S&P 500 index using the GARCH-MIDAS models.

	MSE	MAE	HMSE	HMAE	QLIKE
Model 0	**0.627**	0.007	0.025	0.000	0.000
Model 1	**0.655**	0.008	**0.207**	0.001	0.001
Model 2	**0.633**	0.007	0.083	0.000	0.000
Model 3	**0.885**	0.007	**0.207**	**0.342**	0.001
Model 4	**0.595**	0.012	**0.178**	0.006	0.000
Model 5	**0.962**	0.007	**0.221**	**0.342**	**0.224**
Model 6	**0.627**	0.007	**0.178**	0.034	0.000
Model 7	**0.773**	0.008	0.004	0.000	0.003
Model 8	**0.655**	0.007	0.099	0.006	0.000
Model 9	**0.775**	0.007	**0.207**	0.006	0.012
Model 10	**0.773**	0.008	**0.207**	**0.342**	0.005
Model 11	**0.609**	0.008	**0.207**	0.031	0.004
Model 12	**0.773**	**1.000**	0.000	0.000	0.004
Model 13	**0.837**	0.008	0.141	0.000	**0.737**
Model 14	**0.775**	0.008	**0.588**	**1.000**	**0.737**
Model 15	**1.000**	0.008	**1.000**	**0.342**	**1.000**

Notes: The typology of the models is given in Table 1. The numbers in the table are the *p*-values. Numbers larger than 0.10 are indicated in bold and underlined, and suggest that the corresponding model performs significantly better among the model set.

Findings:

- **Model 15:** Best overall performance, particularly in MAE, HMSE, and QLIKE.
- **Models 5 and 13:** Strong performance across several metrics.
- **Models 3, 7, and 11:** Perform better than the benchmark model (Model 0) in most tests.

Implications:

- Incorporating asymmetry and extreme volatility effects leads to better predictive accuracy.
- Enhanced models outperform the standard GARCH-MIDAS model across multiple evaluation criteria.

Table 4
Results of the Diebold–Mariano test between Model 0 and Models 1–15.

	MSE	MAE	HMSE	HMAE	QLIKE
Model 1	0.950* (−1.38)	0.976*** (−2.570)	0.900*** (−2.813)	0.960*** (−5.139)	0.942*** (−7.774)
Model 2	1.001 (0.426)	0.997*** (−6.576)	1.001 (0.361)	1.002 (7.171)	1.000 (0.100)
Model 3	0.946* (−1.46)	0.982** (−1.996)	0.869*** (−2.989)	0.953*** (−6.306)	0.950*** (−6.842)
Model 4	0.997 (−0.150)	1.001 (1.847)	0.998 (−0.998)	0.999 (−1.130)	0.999 (−0.645)
Model 5	0.944* (−1.403)	0.976*** (−2.448)	0.869*** (−3.201)	0.951*** (−5.933)	0.935*** (−8.014)
Model 6	0.999 (−0.313)	0.994*** (−6.945)	0.975 (−0.992)	0.999 (−0.072)	0.997* (−1.492)
Model 7	0.953* (−1.455)	0.971*** (−3.12)	0.922** (−2.252)	0.970*** (−3.898)	0.941*** (−7.909)
Model 8	1.001 (0.027)	0.999 (−0.035)	1.034 (1.105)	1.013 (1.894)	0.994 (−0.822)
Model 9	0.951* (−1.500)	0.966*** (−3.931)	0.881** (−2.266)	0.969*** (−3.912)	0.939*** (−7.976)
Model 10	0.951* (−1.343)	0.981** (−2.137)	0.907*** (−2.648)	0.962*** (−5.011)	0.950*** (−6.798)
Model 11	0.952* (−1.406)	0.980*** (−2.332)	0.883** (−2.201)	0.963*** (−4.963)	0.950*** (−6.846)
Model 12	0.984 (−0.392)	0.860*** (−9.406)	2.265 (6.777)	1.357 (12.912)	1.076 (2.755)
Model 13	0.946* (−1.612)	0.964*** (−4.299)	0.885*** (−2.746)	0.962*** (−4.737)	0.932*** (−8.534)
Model 14	0.950 (−1.249)	0.978** (−2.198)	0.853** (−2.160)	0.959*** (−4.595)	0.933*** (−7.733)
Model 15	0.943** (−1.605)	0.961*** (−4.421)	0.832** (−2.120)	0.959*** (−4.675)	0.927*** (−8.426)

Conclusion

- Incorporating asymmetry and extreme volatility effects in GARCH-MIDAS models significantly improves volatility forecasts.
- Enhanced models aid in better financial risk management and investment decisions.
- Results demonstrate robustness across different market conditions and datasets.
- Improved model accuracy supports more informed decision-making in volatile markets.
- Provides new insights into the impact of extreme events and news asymmetry on stock volatility.
- Highlights the importance of accounting for both short-term and long-term components in volatility modeling.