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Volatility Forecasting in Practice: Evidence from European Hedge Funds

1. Introduction

A large strand of research investigates the performance, risk, and characteristics of hedge funds. Beginning with Agarwal and Naik (2000), this journal alone has published dozens of articles about the hedge fund industry in recent years. Despite this keen interest, our knowledge about the decision-making of this group of money managers is still limited. In a similar vein, extensive research examines the determinants and predictability of financial market volatility, but only anecdotal evidence exists on how market participants actually predict volatility in day-to-day operations. While empirical work has established a strong stance in academia that option implied volatility outperforms time-series forecasting models in terms of predictive power and informational content, the extent to which practitioners share this view remains largely unknown (Poon and Granger 2003, 2005). This research note fills this gap in the literature in that it offers new insight into the forecasting practices of the hedge fund industry. In particular, we present survey evidence from thirty-eight European hedge funds on their use of different forecasting models and discuss their motivations behind model selection. Findings provide a unique glimpse behind the scenes of an industry that has been known for its limited disclosure and may be beneficial to practitioners and academics alike.

2. Survey and Sample

An online questionnaire was emailed to 1,038 employees of 543 distinct hedge funds based in the United Kingdom (UK), Switzerland (CH), Luxembourg (LU) and Ireland (IE) in order to find out **(i)** which volatility forecasting models are used in different capital markets and over varying forecasting horizons and **(ii)** why some models are perceived to be superior to others.

The raw data on this cross-section was acquired from the hedge fund database *Eurekahedge* and email addresses were obtained through secondary research. The questionnaire can be found online at: kclbs.qualtrics.com/SE/?SID=SV_6DqU9S4BpOzOJSZ. We received thirty-nine valid replies that represent 38 different hedge funds, resulting in an overall 7.0% response rate (see Table 1). Unit non-response is a common phenomenon when surveying investment professionals and high-level executives about their proprietary strategies and techniques. For instance, Bancel and Mittoo (2004) report a total of 29 responses for their survey of European chief financial officers and Lerner and Schoar (2005) gather data from 28 private equity funds. Our response rate is also consistent with Graham and Harvey (2001) who survey chief financial officers and report a 9.0% response rate, respectively.[1]

[Insert Table 1 about here]

The questionnaire followed Poon and Granger's (2003, 2005) categorisation of forecasting models and described the four categories to participants as follows;

(1) HISVOL: ***:*** *Historical volatility models such as Exponential Moving Average, Ordinal Least Square regressions;*

(2) GARCH: GARCH-family models such as ARCH, GARCH(1,1), TGARCH and so forth;

(3) SV: Stochastic volatility models that are non-GARCH-family models;

(4) IV: Implied volatility models that is option implied volatility observed in derivative markets.

Reviewing 66 articles that offer a pairwise comparison between different forecasting models, Poon and Granger (2005, p. 46) show that IV models outperform HISVOL and GARCH models

[1] It should also be noted that the sample may not be free from self-selection bias, but due to the anonymous nature of our survey this bias cannot be quantified.

in 76% and 94% of studies, respectively, and conclude that IV "provides the best forecasts, followed by HISVOL and GARCH with roughly equal performance, although HISVOL may perform somewhat better." Recent evidence is in general consistent with these global results. In studying sixteen FTSE100 stocks, Garvey and Gallagher (2012) find that the predictive power of IV is at least equal, and in some instances even greater, than for GARCH family models. Silvey (2007) shows that out-of-sample, HISVOL models often outperform GARCH models in terms of estimation accuracy.[2] Revealing the extent to which these empirical findings are in line with investors' practice is the main purpose of our questionnaire. In doing so, we survey participants not only on model use in different markets and over varying forecasting horizons, but also invite comments on their reasons for prioritising certain models over others.

Figure 1 presents summary statistics for our final sample. The strong educational background of our respondents (MBA: 26%; Taught Postgraduate: 22%; PhD: 15%) supports the assumption that hedge fund executives, managers and analysts have adequate prior knowledge about volatility forecasting techniques. The vast representation of high hierarchy personnel in the sample (Executives 38%; Fund managers: 49%) accredits respondents' replies and endorses the credibility of the results. Furthermore, the participating funds' pursue a wide range of investment strategies which we aggregate into different market exposure categories (see Fig.1.IV), and assets under management (AUM) information on the fund level (self-reported by participants) is displayed in Fig.1.V. The average fund size in our sample is \$191.3M (median: \$88.0M, standard deviation: \$214.1M) and the average AUM for the population of 543 hedge funds is \$522.2M (median: \$50.0M, standard deviation: \$1,911.0M). Untabulated t-tests show that the size difference between the sample and population is insignificant (p-value: 0.388), corroborating that self-selection bias is limited. Moreover, our average fund size compares well

[2] See also Ammann, et al. (2009) who demonstrate for a large sample of US stocks that IV outperforms HISVOL models in predicting future stock returns.

with descriptive statistics in Khelifa and Hmaied (2014) who analyse the European hedge fund industry over time and report an average fund size of $101.1M as of December 2012.[3] Finally, about half of the respondents in our sample actively consider volatility forecasts in their decision-making (see Fig.1.VI).

Panels VII-IX indicate the relative importance of volatility forecasts for the hedge funds in our sample.[4] As predicted by the literature (for example, Christoffersen and Diebold, 2000; Poon and Granger, 2003, 2005) volatility forecasts are greatly used for purposes associated with risk management (76%), trading and investment strategy development (71%), derivative and product pricing (57%), but less important for stock valuation (10%) purposes (see Fig. 1.IX). The majority of funds update their forecasts on a daily (39%) to weekly (22%) basis and predominantly apply proprietary forecasting solutions to predict volatility. Thus, it can be said that among the volatility forecasting users, volatility forecasts constitute an integral part of the operational and strategic decision making process in those funds.

In summary, the variation in respondents' and fund characteristics allows for a rich description of volatility forecasting practices and benefits our investigation as to whether practitioners' actions are consistent with academic evidence.

[Insert Figure 1 about here]

[3] Average fund size is based on 1,619 European funds with combined assets of $163.7 billion as of December 2012 (Khelifa and Hmaied, 2014, p. 47-8).

[4] Only those participants who answered yes to the question as to whether they use volatility forecasts, were given the chance to provide information about panel VII, VIII and IX, respectively.

3. Results

3.1 Model Use in Different Capital Markets

To pinpoint which forecasting models are used in different capital markets, we asked participants to indicate which model categories (viz. HISVOL, GARCH, SV, IV) they viewed as most relevant to forecast volatility in equity, debt, foreign exchange (FX), commodities and derivatives markets (for each market multiple models could be selected).

Figure 2 shows that IV and HISVOL models are considered to be most likely to predict future volatility throughout all markets by our respondents. Even if GARCH and SV models – given their comparable nature – are aggregated into one variable, HISVOL and IV models remain of utmost relevance to participants (see Fig. 2.I). Results further illustrate a tendency among respondents to use more than just one model to predict future volatility in the respective markets; that is, the average participant uses 1.48 forecasting models in equity, 1.75 in FX, 1.50 in commodities, 1.33 in debt and 1.40 in derivatives markets. This provides some insights into how models are actually operationalised by participants. As the vast majority of responses pertain to equity markets, our subsequent analyses focus on this capital market primarily.

[Insert Figure 2 about here]

As illustrated in Figure 3.I, two-thirds of respondents rely on one model only to predict volatility, whereof 52% (35%) use IV (HISVOL) models to calibrate their single-model forecasting approach. About one-third of respondents pursue a multi-model forecasting approach, whereof 26% merge HISVOL+IV+GARCH/SV models into one multi-model forecasting solution. Eventually, these multi-model approaches can be traced back to and staggered around their origin (see Fig. 3.III). The interpretation of Figure 3.III is as follows; (i) in 93% of the cases

HISVOL models are the origin of any model combination, (ii) in 59% of the cases HISVOL and IV models together are either the origin of model combinations (i.e. GARCH/SV models are supplemented) or used as an exclusive dual-model forecasting approach (analogous interpretation for HISVOL+GARCH/SV applies) and, (iii) in 26% of the cases all three models are used together to predict volatility. Figure 3.II highlights the overall model representation and shows how frequently a specific model is used, irrespective of whether it serves as input to a single- or multi-model forecasting solution. Overall, findings tend to confirm a strong agreement between prevailing practice and academia regarding IV models' superiority; however, there is also strong evidence that HISVOL models are of much greater importance to practitioners than one might have inferred from recent empirical work.

[Insert Figure 3 about here]

3.2 Model Use over Different Forecasting Horizons

To examine the impact of different forecasting horizons on model use in practice, we asked participants to specify which models (viz. HISVOL, GARCH, SV, IV) are most relevant to them in forecasting volatility over a day, week, month, year and beyond one year. Multiple selections were possible and the survey allowed participants to indicate the irrelevance of a forecasting horizon (see Fig. 4).

[Insert Figure 4 about here]

The following results are particularly noteworthy; firstly, the fine convex dotted line at the top of Figure 4 indicates that very short and very long forecasting horizons are of less relevance to the majority of respondents. Secondly, GARCH/SV models show a comparable trend to HISVOL up to one month, before those models lose much of their importance. This observation is also in line with academic findings that GARCH models lead to "excellent short-term forecasts, but poor long-term forecasts" (Lamoureux and Lastrapes, 1993, p. 323). Thirdly, IV models are most frequently used up to one month, but considerably decrease in attractiveness over longer forecasting horizons; one might explain this observation by the expiration structure of options given that long-term contracts are less frequently traded (i.e. stale prices are common) and, thus, subsume less *volatility expectation* than options with smaller time premiums (Whaley, 1993); another explanation might be the global popularity of implied volatility indices (e.g. CBOE VIX) which report markets' one-monthly volatility expectations and, therefore, might have had a normative impact on forecasting practice.[5] So, irrespective of the appropriate forecasting horizon, it might simply be *best-practice* or *sheer habit* to predominantly use IV predictions up to one month, but not beyond that horizon. To corroborate the soundness of these arguments, supplemental survey evidence would have had to be collected. Finally, HISVOL models are preferably used over medium to long forecasting horizons which might be attributable to these models econometric characteristics in that extreme phases of volatility influence HISVOL predictions less severely than those of the other models in question. This conjecture also tends to be shared by some respondents:

> *"For my purposes 'sensible' is more important than 'accurate' and it is important to avoid the excess fears that are built into IV after big market events so I prefer a simple historic estimate."*

[5] See, for instance, Arak and Mijid (2006) and Bandopadhyaya and Jones (2006) for a discussion of the VIX index.

As the respective models gain and lose in relevance over time, preceding results indicate an overall sensitivity of respondents to different forecasting horizons. However, it is equally important to investigate how varying time spans (analogous to results in Fig. 3) influence model use. Figure 5.I shows the relationship between multi-model and single-model forecasting approaches over different forecasting horizons and reveals that multi-model approaches are slightly increasing with time. In Figure 5.II we further refine these results and reveal that IV models – as a stand-alone solution – experience great support up to one month, before they are mainly considered supplemental models for multi-model forecasting solutions. GARCH/SV combinations are widely underrepresented over very short horizons, however, have a marked influence on multi-model solutions over the medium-range (week-month). Most remarkable is the role HISVOL models constantly play over time. Respondents not only view HISVOL models as the most relevant *companion* to multi-model forecasting solutions, but also as their preferred single-forecaster over medium to long time spans:

> "*What matters in the market is NOT what one thinks; what matters is what the preponderant majority of other participants think - and they tend to think along HISVOL lines.*"

The most pressing question in the context of this study is as to why respondents – somewhat in contradiction to academic findings – are so extremely focused on HISVOL models? In disclosing participants' motivations behind model choice in the final results section of this article, we attempt to partially answer this question.

[Insert Figure 5 about here]

Returning to the impact of varying time spans on participants' forecasting behaviour, it still needs to be seen as to what extent the individual participant alters model use over time. Based on academic results that some models produce better forecasts over shorter (GARCH/SV), and others are more precise over longer horizons (HISVOL/IV); it could well be envisaged that participants make use of the individual strength of the respective models by using different forecasting solutions over varying forecasting horizons. If this conjecture holds, then there should be no significant association between a respondent's daily and weekly model use, weekly and monthly use and so forth.[6] High levels of correlation between model use over varying horizons tend to reject this supposition which indicates that participants remain greatly loyal to their preferred forecasting solution, whatever the forecasting horizon may be (see Table 2). This finding, however, should not be mistaken as proof of uniformity in forecasting solution calibration. It certainly remains a possibility that *within* a particular solution each model is assigned a different influence/weight, depending on which horizon volatility is predicted. Such considerations might need preliminary clarification, before one can develop a *best-practice* forecasting solution.

[Insert Table 2 about here]

3.3 Participants' Motivations for Model Selection

The more stimulating responses in survey research often stem from open-end questions. Therefore, we first encouraged participants to rank the model categories according to perceived forecasting performance (Figure 6 shows the final ranking and confirms previous findings of IV and HISVOL prevalence on their merits), afterwards we asked participants to elucidate why

[6] See Appendix 3 for frequencies of forecasting approaches over different forecasting horizons in equity markets.

they view their highest ranked model as superior in comparison to the other models. We assigned each answer to one or more generic categories (see Appendix 4) and summarized the outcome of this coding-process in Figure 7.

[Insert Figure 6 about here]

In approximately eighty percent of the cases, respondents find strong positive arguments to rank IV models in the top position. Those who did, most frequently reason in favour of the ability of IV models to capture market sentiment and, further, stress these models ability to generate *"superior forward predictions"* (see Fig. 7.I). Perceived limitations of the other models in question strengthen participants' belief in IV models further (*"Complex models do not make a complex phenomenon easier to understand, they just hide the many additional assumptions required")*.

Those who ranked HISVOL models the highest, most frequently emphasise that model characteristics (e.g. *"underlying mean reversion", "less sensible to overfitting"*), the simplicity to operationalise such models, limitations of other models (*"I'm not convinced Garch or SV add value", "I disbelieve in general in statistical prediction"*) are decisive reasons to opt for HISVOL (see Fig. 7.II). A wide use of within the industry (*"[...] the preponderant majority of other participants [...] tend to think along HISVOL lines.")* serves as an additional factor to rely on HISVOL models and is consistent with the Keynesian beauty contest: "It is not a case of choosing those [faces] that, to the best of one's judgment, are really the prettiest, nor even those that average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average opinion to be" (Keynes, 1936, p. 189). Comparable reasons are given for GARCH/SV (see Fig. 7.III).

[Insert Figure 7 about here]

By and large, our evidence supports findings from previous sections and recent empirical work. For instance, participants who perceive IV to be superior to other forecasting techniques attribute this performance advantage to its forward-looking and market-sentiment capturing nature which coincides with academic reasoning (for example, Christensen and Prabhala, 1998; Christensen and Hansen, 2002). What is more, the above helps to put into perspective the stark representation of HISVOL models throughout markets and time. On the one hand, participants' answers reveal a certain demand for simple, but trusted forecasting solutions – which HISVOL models certainly are. On the other hand, responses might be interpreted as hedge funds not being HISVOL proponents *per se*, but merely surrendering to the *thinking of the markets*. This joint evidence might then explain the overall popularity of HISVOL among survey participants.

4. Summary and Conclusion

In this study we surveyed thirty-eight European hedge funds on their use of volatility forecasting models and aimed to study their motivations for preferring one model over another. In summary, our results show that for most of our hedge funds volatility forecasts play a vital role in their daily operations with forecasts being predominantly used for risk management, strategy development, and pricing purposes. The average respondent shows an inclination to rely on multi-model forecasting solutions and most of the participating hedge funds project equity market volatility over medium term periods (weeks to months).

Irrespective of the forecasting horizon and capital market, survey response endorsed the academic proposition of IV model superiority, but also showed that HISVOL models are of much greater relevance to participants than one might have inferred from the normative econometric literature. This stark representation in itself tends to emerge from the *notorious HISVOL thinking* of the market and poses the question 'what market participants have learnt from past failures of historical models?' Stated differently, if history is an imperfect guide for the future, might IV then become the new HISVOL? As some weak (unreported) evidence exists, younger participants are more inclined to rely on IV predictions than older ones. Could this greater acceptance of IV among the younger generation then trigger a regime shift in forecasting practice over the long run?

While these results might need confirmation on a larger scale, we conclude that prevailing practice urges for a sensible, market sentiment capturing forecasting solution that reduces model complexity. Although multi-model forecasting solutions tend to be well-embedded in the day-to-day operations of hedge funds – supported by both qualitative (*"I tend to use two-factor vol models")* and quantitative survey evidence (see Figure 3 and Figure 6) – academic research taking into account the "mix and match" solutions of practitioners is still scarce. Another interesting avenue for future research might be to examine the link between model choice and hedge funds' performance and characteristics – an analysis we could not perform due to the anonymous nature of our survey.

Appendix

Appendix 1: Model Use in Different Markets by Model Categories

This table shows response and case frequencies to the question: *Irrespective of forecasting horizons which category of models (multiple selection possible) is most relevant to your fund in regard to the following markets?*

Absolute Numbers	**IV**	**HISVOL**	**GARCH**	**SV**	**Total Responses**	**Cases**
Overall	58	58	25	17	158	106
Equity	45	45	18	12	120	81
FX	5	5	3	1	14	8
Commodities	3	3	1	2	9	6
Debt	2	4	1	1	8	6
Derivatives	3	1	2	1	7	5
Relative Numbers	**IV**	**HISVOL**	**GARCH**	**SV**	**Total Responses**	**Cases**
Overall	55%	55%	24%	16%	149%	100%
Equity	56%	56%	22%	15%	148%	100%
FX	63%	63%	38%	13%	175%	100%
Commodities	50%	50%	17%	33%	150%	100%
Debt	33%	67%	17%	17%	133%	100%
Derivatives	60%	20%	40%	20%	140%	100%

Appendix 2: Model Use over Different Forecasting Horizons in Equity Markets

This table shows response and case frequencies to the question: *In regard to equity markets which category of models (multiple selection possible) is most relevant to your fund to forecast volatility up to a day, week, month, year and beyond one year?*

Absolute	**IV**	**HISVOL**	**GARCH**	**SV**	**not relevant**	**Total Responses**	**Cases**
1 day	7	5	3	2	20	37	32
1 week	12	8	5	2	15	42	33
1 month	13	12	6	3	14	48	36
1 year	8	11	2	2	17	40	33
> 1 year	5	9	2	3	18	37	31
Total	*45*	*45*	*18*	*12*	*84*	*204*	*165*
Relative	**IV**	**HISVOL**	**GARCH**	**SV**	**not relevant**	**Total Responses**	**Cases**
1 day	22%	16%	9%	6%	63%	116%	100%
1 week	36%	24%	15%	6%	45%	127%	100%
1 month	36%	33%	17%	8%	39%	133%	100%
1 year	24%	33%	6%	6%	52%	121%	100%
> 1 year	16%	29%	6%	10%	58%	119%	100%
Total	*27%*	*27%*	*11%*	*7%*	*51%*	*124%*	*100%*

Appendix 3: Forecasting Approaches over Different Forecasting Horizons in Equity Markets

This table shows recoded survey response from Appendix 2. If a respondent indicated that s/he regards HISVOL and IV as most relevant to predict volatility over a day, then this answer is recoded into the single variable HISVOL-IV (and so forth). This is done over all forecasting horizons, before the sum over all horizons is taken as an overall indication for model combinations in equity markets; thus, response numbers equal cases analysed.

Absolute	**Day**	**Week**	**Month**	**Year**	**> Year**	**Overall**
Single-Model Approach	9	13	13	10	9	54
IV-Single	5	8	8	4	3	28
HISVOL-Single	3	3	3	5	5	19
GARCH/SV-Single	1	2	2	1	1	7
Multi-Model Approach	3	5	9	6	4	27
HISVOL+IV	0	1	3	4	1	9
HISVOL+GARCH/SV	1	1	4	2	1	9
IV+GARCH/SV	1	0	0	0	1	2
HISVOL+IV+GARCH/SV	1	3	2	0	1	7
Total	*12*	*18*	*22*	*16*	*13*	*81*
Relative	**Day**	**Week**	**Month**	**Year**	**> Year**	**Overall**
Single-Model Approach	75%	72%	59%	63%	69%	67%
IV-Single	56%	62%	62%	40%	33%	52%
HISVOL-Single	33%	23%	23%	50%	56%	35%
GARCH/SV-Single	11%	15%	15%	10%	11%	13%
Multi-Model Approach	25%	28%	41%	38%	31%	33%
HISVOL+IV	0%	20%	33%	67%	25%	33%
HISVOL+GARCH/SV	33%	20%	44%	33%	25%	33%
IV+GARCH/SV	33%	0%	0%	0%	25%	7%
HISVOL+IV+GARCH/SV	33%	60%	22%	0%	25%	26%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

Appendix 4: Qualitative Factors Influencing Model Choice

After participants ranked model categories according to perceived forecasting performance, we posed the following open-end question: *Why do you think is your highest ranked model superior to its competitors?* The table below reports survey responses (as given and not amended) along with our coding of participants' answers.

Highest Ranked	Respondent		Coding
HISVOL	HISVOL.1	There is an underlying mean-reversion supported by implicit valuation.	✓ Model Characteristics
HISVOL	HISVOL.2	simplicity of use	✓ Simplicity
HISVOL	HISVOL.3	For my purposes "sensible" is more important than "accurate" and it is important to avoid the excess fears that are built into IV after big market events so I prefer a simple historic estimate. I'm not convinced Garch or SV add value over multi-month periods.	✓ Model Characteristics ✓ Simplicity ✓ Limitations of other models
HISVOL	HISVOL.4	Simple and less sensible to overfitting	✓ Simplicity ✓ Model Characteristics
HISVOL	HISVOL.5	Because, as stupid as it is, it is what is used by the majority of market-makers. GARCH is used by risk managers, and SV is used only in vanilla-exotic derivatives pricing (but is arbitrageable because it places the price quoter off-market). IV is driven by Keynesian 'animal spirits' in equity markets, and is a poor predictor of ex-post realised volatility, as well as consistently arbitrageable (selling rich straddles vs. buying cheap wings). What matters in the market is NOT what one thinks; what matters is what the preponderant majority of other participants think -- and they tend to think along HISVOL lines. I have made more than 50,000 multivariate and exotic option prices during my 20-year career, and I was able to be on-market using HISVOL as opposed to anything else (including 'fits' like Dupire local vol, which contain no scientific drivers).	✓ Industry Use ✓ Limitations of other models
HISVOL	HISVOL.6	I disbelieve in general in statistical prediction, so the Historical vol analysys should be less deceiving	✓ Limitations of other models
IV	IV.1	Historically it has given superior forward predictions	✓ Predictive Ability
IV	IV.2	It is capturing market participants positioning	✓ Capturing Market Sentiment
IV	IV.3	When adjusted for risk premium IV captures market participants views in aggregate.	✓ Capturing Market Sentiment
IV	IV.4	I think it's SV.	✓ n/a

IV	IV.5	The market is always right, especially in markets where volatility is actively traded. The problem with volatility models is that they have to be consistent both on the level of the underlying and the level of volatility. When both are traded, they usually cease to make sense. In addition, complex models do not make a complex phenomenon easier to understand, they just hide the many additional assumptions required.	✓ Capturing Market Sentiment ✓ Limitations of other models
IV	IV.6	forward looking	✓ Predictive Ability
GARCH	GARCH/SV.1	Practical use in the field	✓ Industry Use
GARCH	GARCH/SV.2	Works better out of sample	✓ Model Characteristics
SV	GARCH/SV.3	The classification is little bit too simple for how I view vol models in general. Hisvol will under- or over-estimate vol and underperform due to equal weighting schemes, so ranked it worst. But I find the $ value or SR contribution from GARCH or SV littl at best in practice, when compared with easier EWMA-type models. Not sure which one contains more info IV or backward looking models, that is probably debatable, but combining IV and EWMA(or GARCH/SV models) tends to work better (backward and forward comination). Also I prefer range volatility to squared return models (even for RQV type models at high frequency). Finally, all the models above fail forecasting vol horizons beyond a week or so at best, because they tend to capture tail shocks mostly, but tey are relatively silent for cyclical or slow-moving component of vol where excess kurtosis is not so apparent. For long-term forecasting vol, I tend to use two-factor vol models (slow moving factor + tail shock factor) and also use fundamental variables n the equations.	✓ Limitations of other models
Unranked	Unranked.1	We don't use models we trade markets. People who trade models normally end up working for banks and imploding them. No I'm being serious.	

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Table 1

Population Development and Survey Response

This table reports response statistics for this study's survey which was emailed to 1,038 employees of 543 distinct hedge funds based in the United Kingdom (UK), Switzerland (CH), Luxembourg (LU) and Ireland (IE). Distinction is made between personalised (Person.) and generalised (General.) email addresses. The deviation between initial and final population numbers is due to invalid contact details. Invalid personal email addresses were substituted with general email addresses where possible.

	Trial UK		**UK**		**CH-LU-IE**		**UK-CH-LU-IE**		
Number of Contacts	Personal	General	Personal	General	Personal	General	Personal	General	Total
Initial	200	-	565	126	309	80	1074	206	1280
Final	159	9	436	127	227	80	822	216	1038
Final in % of Initial	79.5	-	77.2	100.8	73.5	100.0	76.5	104.9	81.1
Responses	6	-	13	7	11	2	30	9	39
Response Rate in % of Final	3.8	-	3.0	5.5	4.8	2.5	3.6	4.2	3.8
Number of Funds									
Initial	76	-	199	126	112	80	387	206	593
Final	59	9	171	127	97	80	327	216	543
Final in % of Initial	77.6	-	85.9	100.8	86.6	100.0	84.5	104.9	91.6
Responses	6	-	12	7	11	2	29	9	38
Response Rate in % of Final	10.2	-	7.0	5.5	11.3	2.5	8.9	4.2	7.0
Average Contacts per Fund									
Initial	2.63	-	2.84	1.00	2.76	1.00	2.78	1.00	2.16
Final	2.69	1.00	2.55	1.00	2.34	1.00	2.51	1.00	1.91

Table 2

Correlations of Model Use over Different Forecasting Horizons in Equity Markets

This table reports Cramer's V correlations between respondents' model use over different forecasting horizons in equity markets.

Model Use		1 day	1 week	1 month	1 year	> 1 year
1 day	Correlation	1				
	Sig. (2-tailed)	-				
	N	12				
1 week	Correlation	.901***	1			
	Sig. (2-tailed)	.009	-			
	N	10	18			
1 month	Correlation	.875*	.753**	1		
	Sig. (2-tailed)	.060	.032	-		
	N	10	14	22		
1 year	Correlation	.890	.791**	.796***	1	
	Sig. (2-tailed)	.164	.018	.001	-	
	N	10	12	16	16	
> 1 year	Correlation	1.000**	.923**	.776	.878**	1
	Sig. (2-tailed)	.050	.043	.144	.021	-
	N	10	10	13	13	13

Note: ***, **, * denote significance levels at 1%, 5% and 10%, respectively. GARCH and SV is consolidated into one variable.

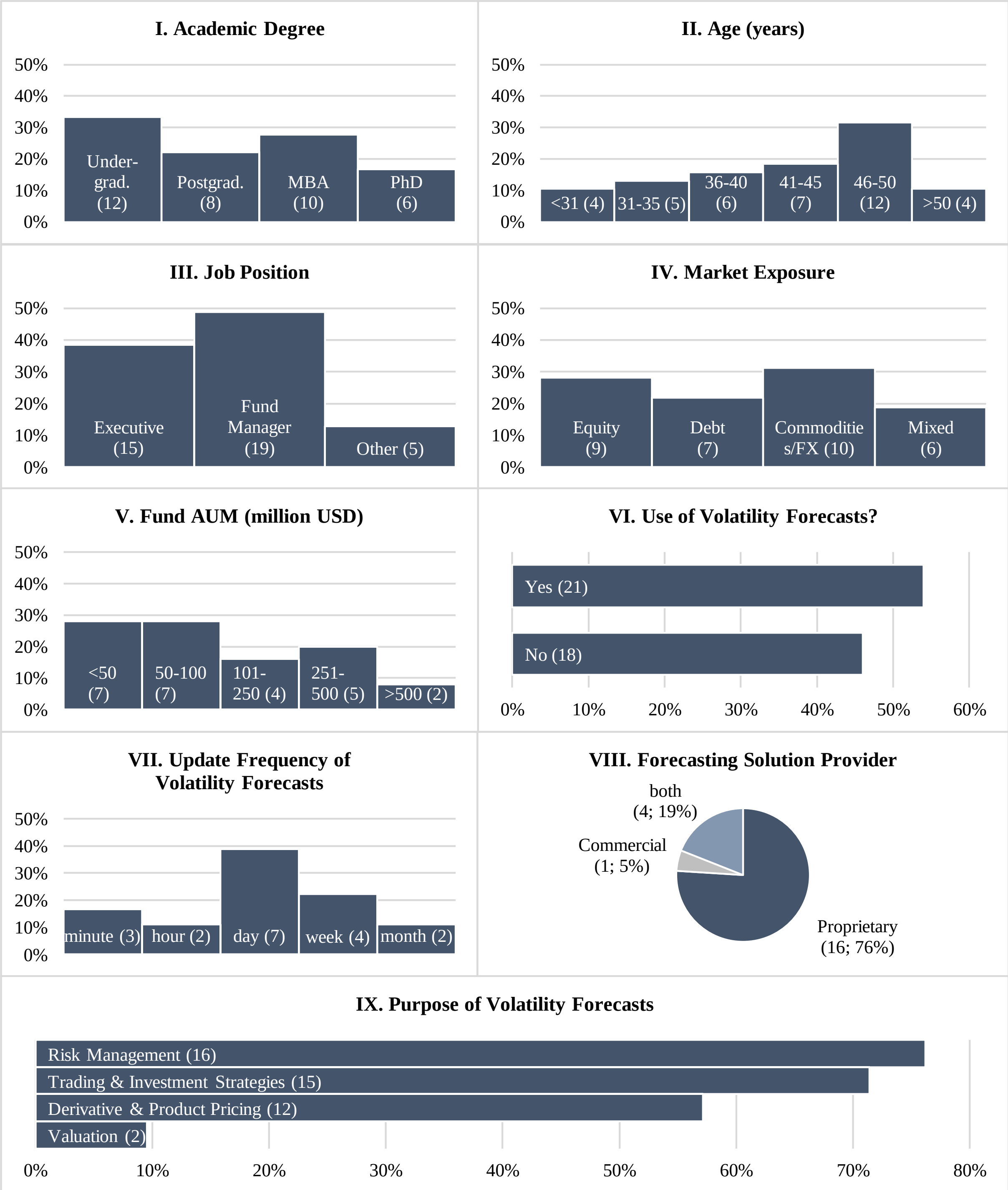


Fig.1. Summary Statistics

This figure provides descriptive statistics for the final sample. Actual number of responses shown in parentheses. Only those participants who answered "yes" to the question as to whether they actively consider volatility forecasts in their decision-making (Panel VI), were given the chance to provide information about panel VII, VIII and IX, respectively. Number of observations are as follows: Panel I: N=36; II: (38); III: (39); IV: (32); V: (25); VI: (39); VII: (18); VIII (21); Panel IX multiple selections possible: 45 responses and 21 cases.

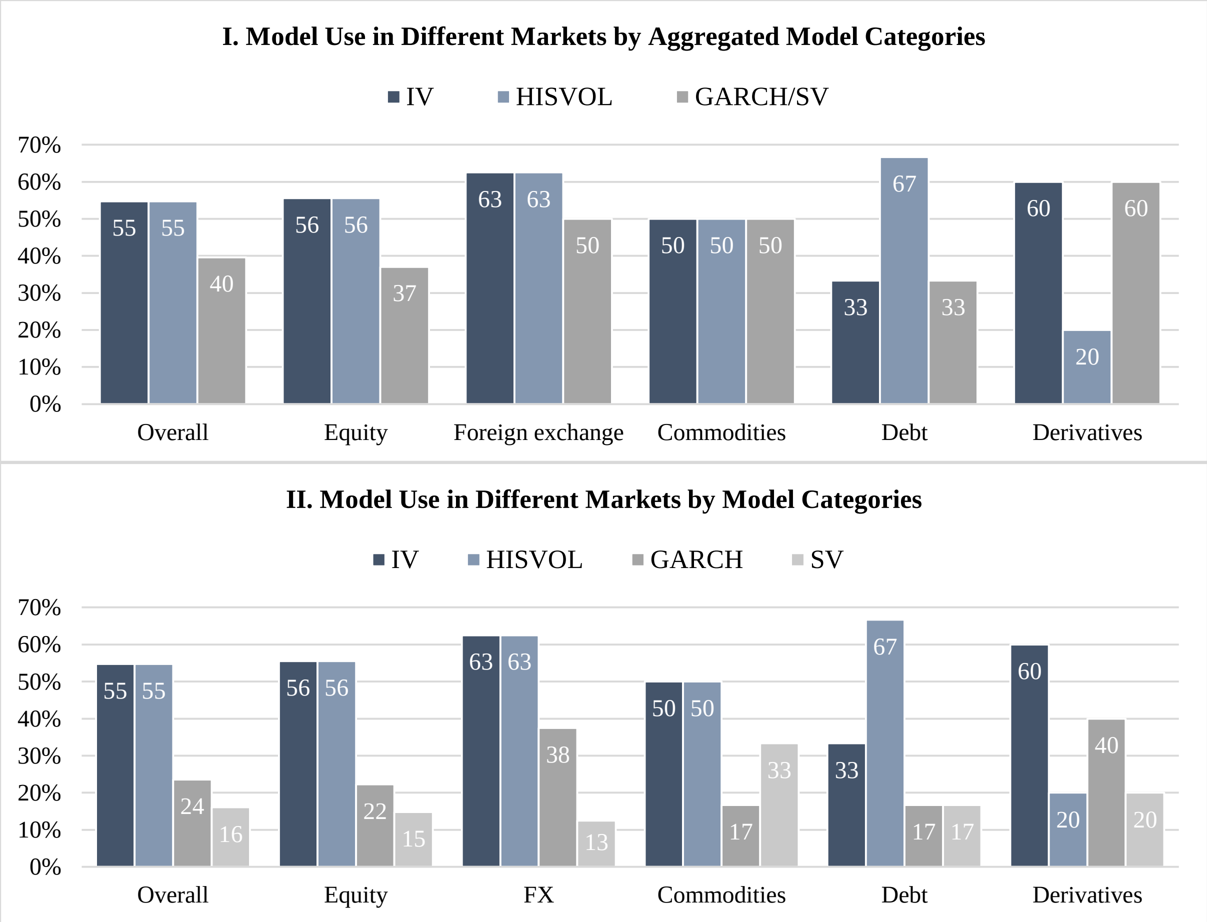
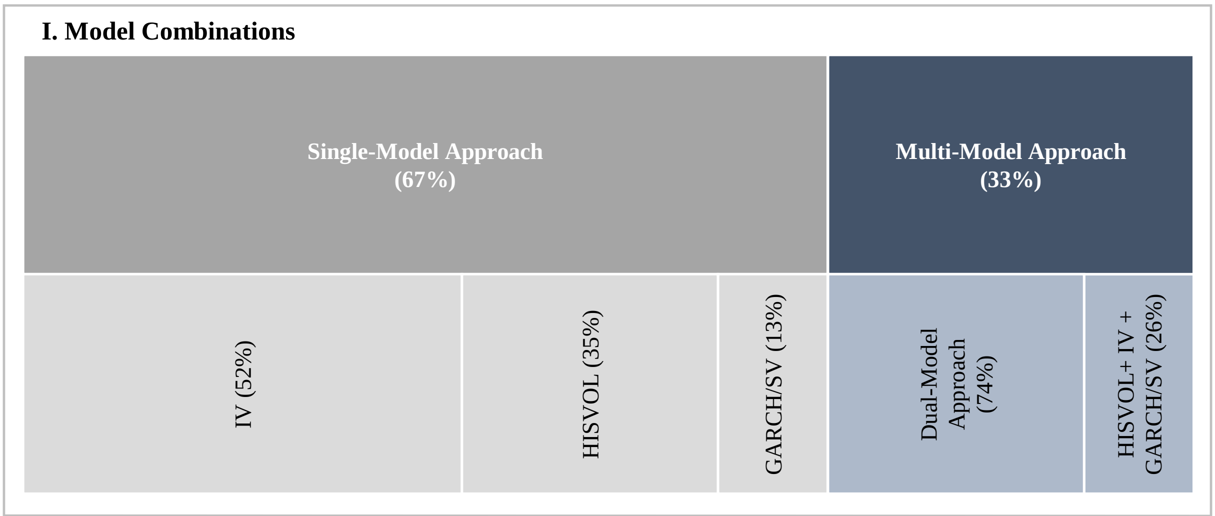
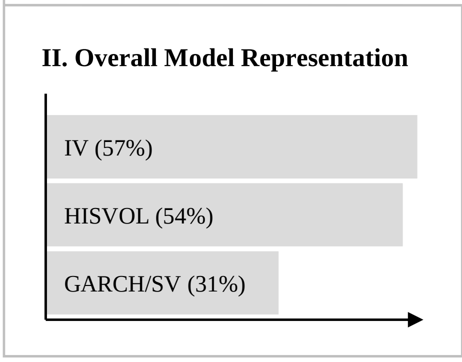


Fig. 2. Model Use in Different Markets

This figure reports participants' answers to the question which models (viz. HISVOL, GARCH, SV, IV) they view as most relevant to forecast volatility in equity, debt, foreign exchange (FX), commodities and derivatives markets (for each market multiple models could be selected). The figure is based on summarised multiple response sets and data labels are in percentages of total cases (see Appendix 1 for response and case frequencies). Panel I aggregates GARCH and SV into one variable.





III. Origin of Multi-Model Approaches

	+ HISVOL	+ IV	+ GARCH/SV
HISVOL	**93%**	59%	59%
IV	59%	**67%**	33%
GARCH/SV	59%	33%	**67%**

Fig. 3. Model Use in Equity Markets

This figure summarises participants' model use in equity markets and is based on responses statistics as reported in Appendix 3. Panel I provides information on how respondents combine different models when predicting volatility. Panel II shows how frequently a specific model is used, irrespective of whether it serves as input to a single- or multi-model forecasting solution. Panel III traces multi-model forecasting solutions back to their origin; e.g. in 59% of the cases HISVOL and IV models together are either the origin of model combinations (GARCH/SV models are supplemented) or used as an exclusive dual-model forecasting approach.

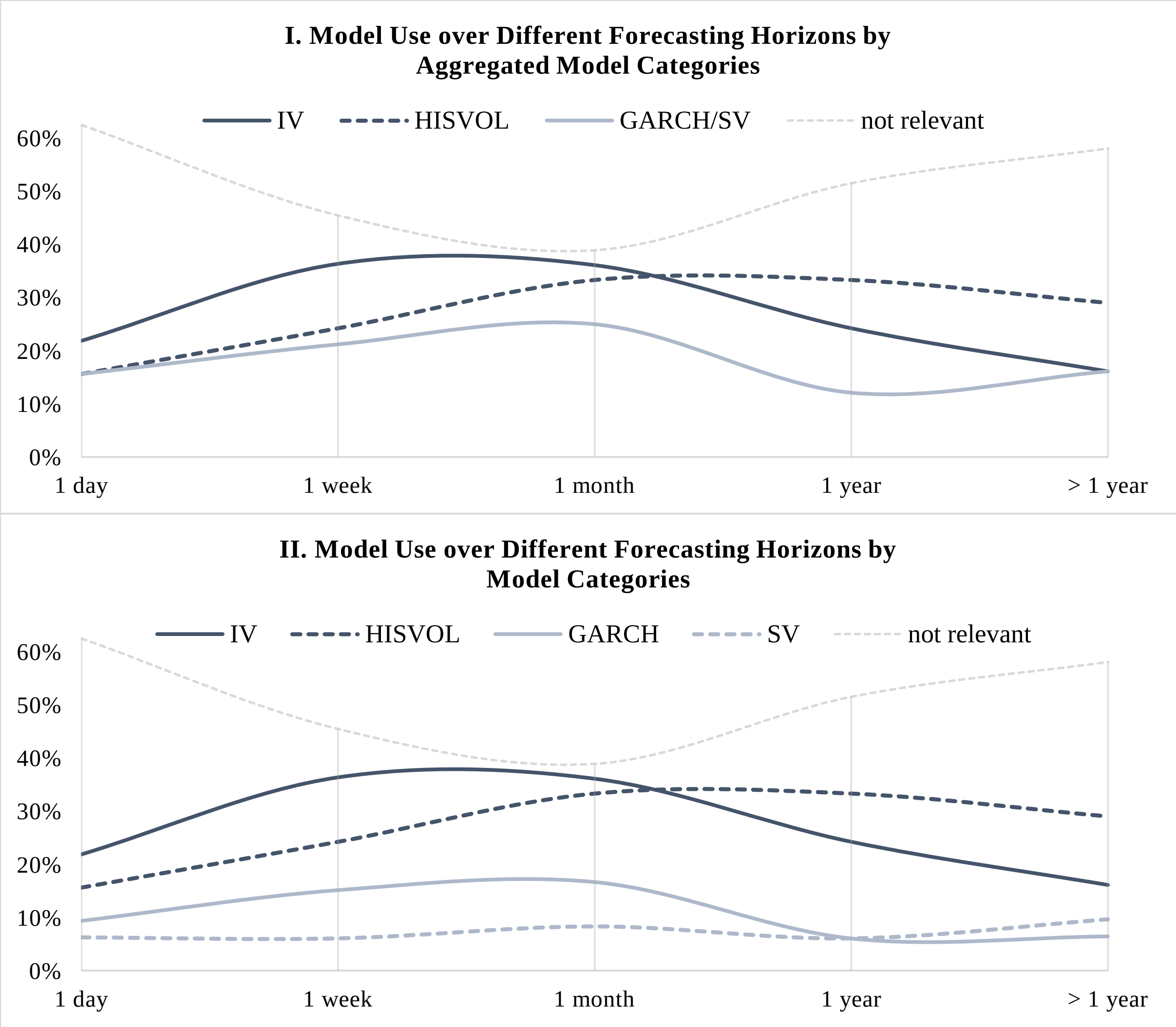


Fig. 4. Model Use over Different Forecasting Horizons in Equity Markets

This figure reports participants' answers to the question which models (viz. HISVOL, GARCH, SV, IV) are most relevant to them in forecasting volatility over a day, week, month, year and beyond one year. Multiple selections were possible and the survey allowed participants to indicate the irrelevance of a forecasting horizon. The figure is based on summarised multiple response sets (see Appendix 2 for response and case frequencies). Panel I aggregates GARCH and SV into one variable.

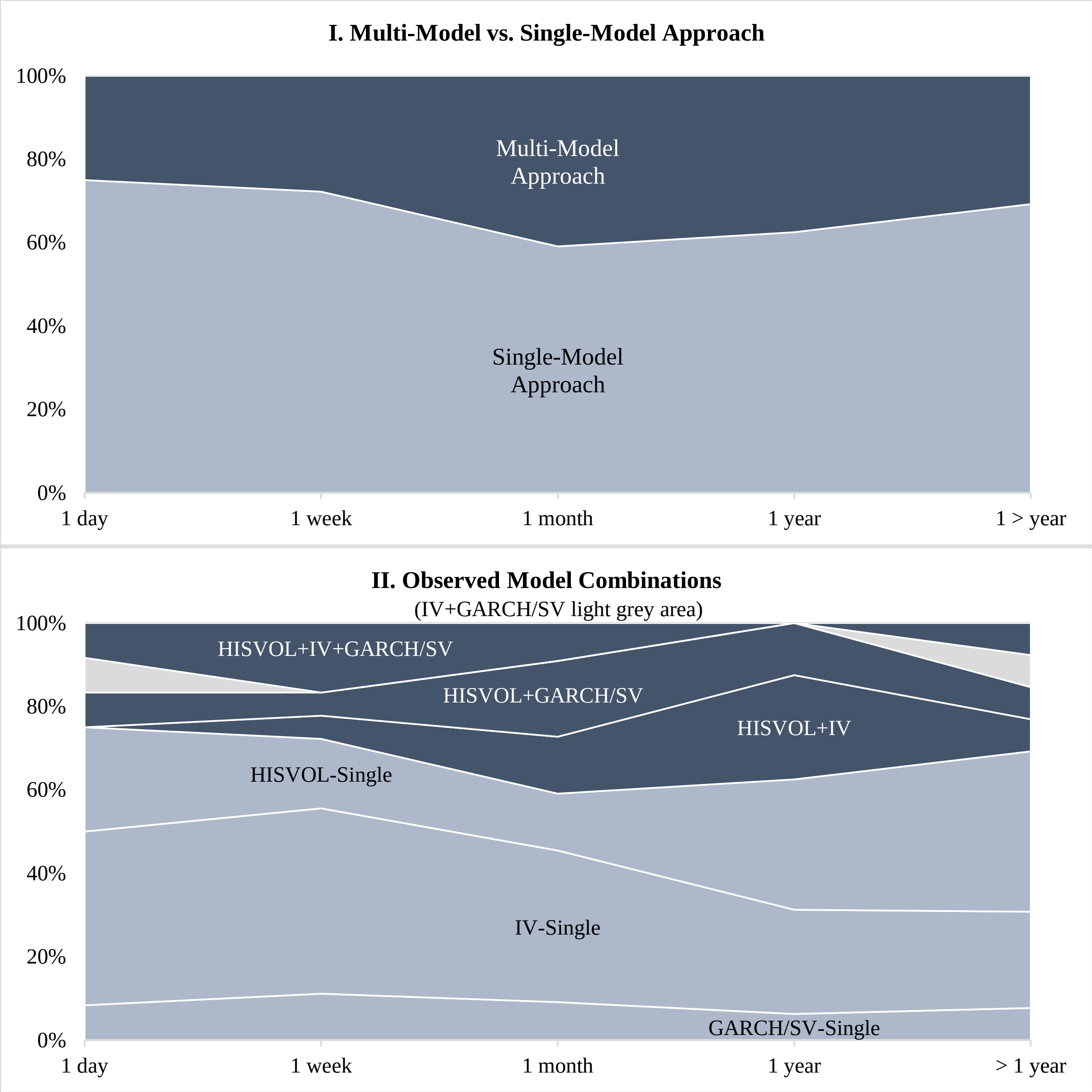


Fig. 5. Forecasting Approaches over Different Forecasting Horizons in Equity Markets

Panel I of this figure shows the relationship between multi-model and single-model forecasting approaches over different forecasting horizons in equity markets. Panel II refines these findings and reports participants’ model combinations over time. Figure is based on response figures in Appendix 3.

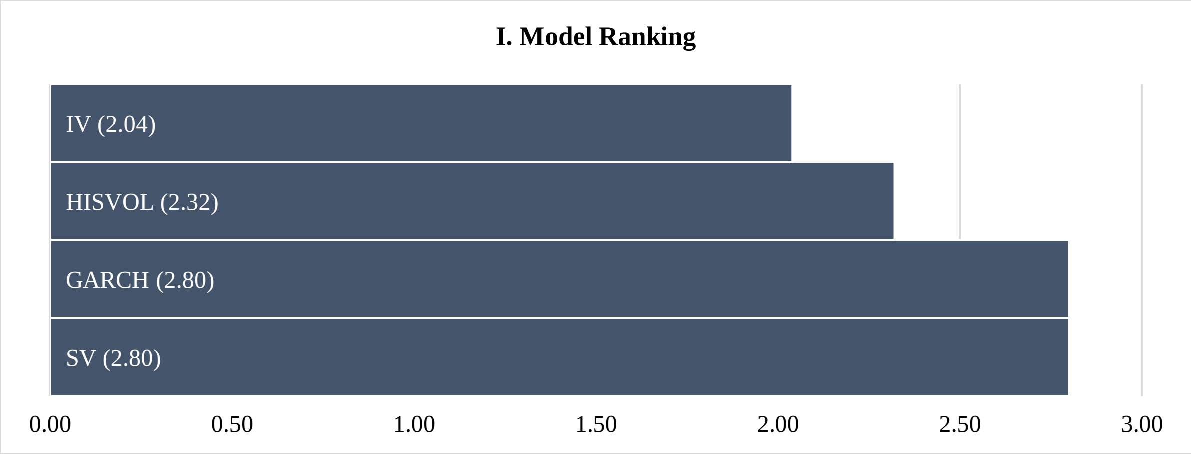


Fig. 6. Forecasting Model Ranking

The survey asked participants to arrange the models (viz. HISVOL, GARCH, SV, IV) in regard to their overall forecasting performance in equity markets. This figure summarises these results and is based on 25 respondents (mean ranking in parentheses).

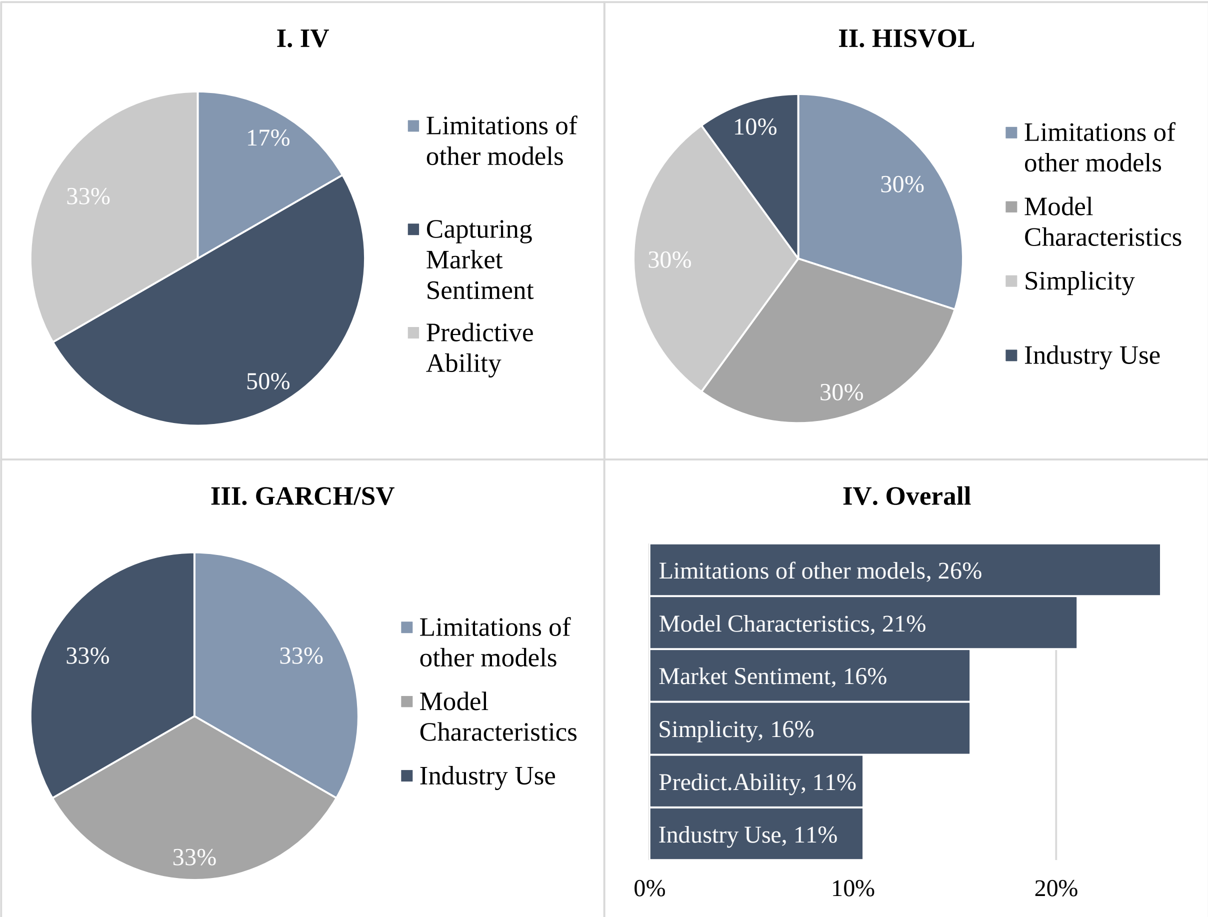


Figure 7: Participants' Motivation for Model Selection

In an open-end question, participants were asked why they view their highest ranked model to be superior in comparison to the other models. We assign each answer to one or more generic categories (see Appendix 4) and show the outcome of this coding-process in this figure. Panel I, II, III are based on six, ten and three responses, respectively, and Panel IV summarises.

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Volatility Forecasting in Practice: Exploratory Evidence from European Hedge Funds

Response to Reviewer's Comments

Thank you for your detailed comments on the previous draft, the thoughtful nature of which helped me improve the paper's focus and exposition. This document summarises my response to each of the points raised in your report. To aid the discussion, I have reproduced each comment from your report below (*italicised text*), followed by an explanation of the corresponding changes made to the revised draft.

Minor Comments

I thank the author for providing detailed explanations related to my concerns. I can see now that not much can be done with respect to the self-selecton bias and fund performance valuation. I would recommend the author to make it clear also for a reader of the paper, that these interesting questions simply cannot be fully addressed. It would be nice to explicitly mention (e.g., in a footnote in the section when the sample is described) that the sample may not be free from a self-selection bias, but this bias cannot be quantified due to the anonymous nature of the survey. Also, in conclusion the author can again reinforce that due to the anonymous nature of the survey, it is not possible to link the reported choice of models by HFs to their performance, but it would be an interesting path for future research.

I have added a footnote on page 2 stating: "It should also be noted that the sample may not be free from self-selection bias, but due to the anonymous nature of our survey this bias cannot be quantified."

On page 12 in the final paragraph of the conclusion, I have added the following sentence: "Another interesting avenue for future research might be to examine the link between model choice and hedge funds' performance and characteristics – an analysis we could not perform due to the anonymous nature of our survey."

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Volatility Forecasting in Practice: Exploratory Evidence from European Hedge Funds

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Abstract

This note provides survey evidence of volatility forecasting practices in a number of European hedge funds. Results confirm the academic consensus that option implied volatility (IV) is a commonly used risk management and volatility forecasting tool among "sophisticated" investors, but also highlight the great popularity of simple historical models whereas stochastic models are of lesser relevance. Sensible, market sentiment capturing forecasting solutions that reduce model complexity are not only demanded, but are also already implemented by a number of practitioners. The development of multi-model forecasting solutions that combine historical and IV information into a reliable predictor of volatility appears to be a promising path for research.

Keywords: *hedge funds; volatility forecasting in practice; survey evidence*

JEL classifications: *C53 Forecasting and Prediction Methods; G31 Financial Risk and Risk Management*

I am grateful to all hedge funds that have participated in this survey. I thank Tarik Driouchi, Alex Preda and an anonymous referee for helpful comments and suggestions on earlier versions of this paper.