Becker, Ralf, Clements, Adam, & Curchin, James (2008) How does implied volatility differ from model based volatility forecasts? In Robinson, T, Christensen, M, & Fletcher, A (Eds.) *Proceedings of the 16th Annual Conference on Pacific Basin Finance, Economics, Accounting, and Management*, 2-4 July 2008, Australia, Queensland, Brisbane.

How does implied volatility differ from model based volatility forecasts?

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Abstract

Much research has addressed the relative performance of option implied volatilities and econometric model based forecasts in terms of forecasting asset return volatility. The general pattern is that implied volatility is a superior forecast. Some authors attribute this to the fact that option markets use a wider information set when forming their forecasts of volatility. An alternative reason may be that the way in which historical data is used differs across the forecasting approaches. This article considers these issues and determines whether S&P 500 implied volatility reflects a set of economic information beyond its impact on the prevailing level of volatility and whether the mapping of historical data varies widely across the approaches. It is found, that while the implied volatility subsumes this information, as do model based forecasts, this is only due to its impact on the current, or prevailing level of volatility. Therefore, it appears as though implied volatility does not reflect a wider information set than model based forecasts, meaning that implied volatility forecasts simply reflect volatility persistence in much the same way of as do econometric models. The manner in which implied volatility maps historical data into a forecast differs from how model based forecasts do so.

Keywords: Implied volatility, VIX, volatility forecasts, informational efficiency.
JEL Classification: C12, C22, G00, G14

Acknowledgements: The authors thank Adrian Pagan whose comments on related work motivated the current research, Stan Hurn for constructive feedback on earlier versions of the article and seminar participants at the Queensland University of Technology

1 Introduction

The behaviour of option implied volatilities have attracted a great deal of research attention. Both the relative forecast accuracy and informational efficiency of implied volatilities (IV) have been considered by numerous authors.

Fleming (1998), Jiang and Tian (2003) and Becker, Clements and White (2006, 2007), amongst others have examined whether various IV measures subsume historical information (predominantly return data) commonly used when forecasting volatility. While Fleming (1998) and Jiang and Tian (2003) find that IV is efficient with respect to such information, Becker, Clements and White (2006) find that S&P 500 IV does not completely subsume a diverse set of information including model based forecasts (MBF). Becker, Clements and White (2007) find that IV contains no information beyond volatility persistence as captured by MBF. While these results are important, we still do not truly understand the fundamental differences between IV and MBF. This paper seeks to redress this.

Poon and Granger (2003, 2005) provide wide ranging surveys of articles comparing various forecasting approaches. The general pattern revealed by Poon and Granger (2003, 2005) is that option based IV produce superior forecasts of volatility relative to competing MBF. Two plausible explanations for this superiority can be proposed. First, Poon and Granger (2003) state that it is of little surprise that IV forecasts are superior as they are based on a larger and timelier information set. Second, it could be argued that the superior forecast performance of IV can be attributed to option markets utilising more complex functions of historical data when forming forecasts, as they are not constrained by a particular function form that maps past volatility information into volatility forecasts.

This paper will investigate whether any empirical evidence exists to support these conjectures. We consider interest rate, commodity price and exchange rate data to establish whether IV incorporates such information that is not routinely[1] included in volatility models. This information has been selected as it could potentially influence option market participants' expectations of future equity volatility.

Volatility forecasts may reflect such information in one of two ways. First, economic information may be reflected in the current level of volatility, and thus both classes of volatility forecasts, MBF and IV may be related to such information. Second, it may be possible that such information informs forecasts beyond its influence on the current level of volatility, an effect only relevant to IV. An approach similar to that used in the informational efficiency studies discussed above is taken to establish in the manner in which such economic information is incorporated into the different volatility forecasts. We establish that the additional economic information considered here is related to the current level of volatility and hence also to all volatility forecasts, be they MBF or IV. More interestingly we establish that some but not all volatility forecasts produce expected volatility changes that are correlated to economic information available at the time of the forecasts. This indicates that only a subgroup of forecasts reflect additional economic information. It is, however, not clearly obvious that IV forecasts are superior in capturing such information.

While all volatility forecasts reflect proxies for historical volatility, MBF do so in a very structured way. Whereas this need not be the case with IV forecasts. Here a simple mapping of past volatility information into the different volatility forecasts reveals that IV does so in a more flexible manner, highlighting a potential advantage of the model free IV approach.

This paper proceeds as follows. Section 2 presents the data relevant to this study. Section 3 outlines the methodology utilized to address the research questions at hand. Sections 4 and 5 present the empirical results and concluding comments

[1] An exception is Glosten, Jagannathan and Runkle (1993), who include interest rate data.

respectively.

2 Data

To address the research question at hand four different sets of data are required. Equity returns, an estimate of IV, realisations of equity volatility and the economic, non-return data, specifically term structure, commodity prices and exchange rate information are utilized here. Each set of data will now be discussed in turn.

The study is based on daily S&P 500 index returns, from 2 January 1990 to 17 October 2003 (3481 daily observations). The implied volatility measure utilized here is that provided by the Chicago Board of Options Exchange, the VIX[2]. The VIX is an implied volatility index derived from a number of put and call options on the S&P 500 index, which generally have strike prices close to the current index value with maturities close to the target of 22 trading days[3]. It is derived without reference to a restrictive option pricing model. For technical details relating to the construction of the VIX index, see Chicago Board of Options Exchange (2003). After allowing for a potential volatility risk premium, the VIX is constructed to be a general measure of the market's estimate of average S&P 500 volatility over the subsequent 22 trading days (Blair, Poon and Taylor 2001, and Christensen and Prabhala, 1998)[4]. As highlighted by Jiang and Tian (2003), the advantages of such a model-free approach to computing implied volatility are two-fold[5]. Relative to a model-based estimate such as Black-Scholes, a model-free estimate incorporates more information from a range of observed option prices.

The measure of actual volatility used here is realised volatility (RV), constructed from intra-day S&P 500 index data (see Andersen, Bollerlsev, Diebold and Labys 2001, 2003 for a discussion of RV)[6]. In dealing with practical issues such as intra-day seasonality and sampling frequency when constructing daily RV_t, the signature plot methodology of Andersen *et al.* (1999) is followed. Given this approach, daily RV_t estimates are constructed using 30 minute S&P 500 index returns.

The set of economic (non-return) information comprises of variables that can be reasonably assumed to reflect general economic conditions and hence influence equity market performance and volatility. The variables are the slope of the term structure represented by the difference between one and ten year US Treasury bond yields (*slope*), the credit spread between BBB rated commercial paper and US Treasury bills (*cspr*), absolute daily oil price change (*oil*) as a measure of volatility in the oil market, and an indicator variable (*doil*) which is unity when the change in oil price is positive and zero otherwise. While this is by no means an exhaustive list of economic variables, they relate to changes in the level of economic activity (*cspr*), inflationary expectations (*slope*) and the headline commodity price in terms of oil prices, which impacts on the cost incurred by many firms and individuals, and thus inflation. These are variables that are available at the daily frequency. The information considered is of a wider nature than that traditionally incorporated in MBF.

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[2]The VIX index used here is the most recent version of the index, introduced on September 22, 2003. VIX data for this study was downloaded from the CBOE website.

[3]The daily volatility implied by the VIX can be calculated when recognising that the VIX quote is equivalent to 100 times the annualised return standard deviation. Hence $(VIX/(100\sqrt{252}))^2$ represents the daily volatility measure (see CBOE, 2003).

[4]Quoting from the CBOE White paper (2003) on the VIX, "VIX [...] provide[s] a minute-by-minute snapshot of expected stock market volatility over the next 30 calendar days."

[5]They utilise a different approach to that embodied into the calculation of the VIX.

[6]Intraday S&P 500 index data were purchased from Tick Data, Inc.

3 Methodology

3.1 Model-based volatility forecasts

The MBF considered here are selected from a range of different model classes frequently applied in the financial econometrics literature. Selected MBF are the GARCH(1,1) (*gar*), an asymmetric GARCH-type GJR threshold model (*gjr*), a stochastic volatility (*sv*) model as well as a short memory (*arma*) and long memory (*arfima*) time-series model of RV. These models are also extended by the inclusion of RV as an additional explanatory variable (*garrv*, *gjrrv*, and *svrv*)[7]. As the VIX is designed as a fixed 22 day ahead forecast, each of the models are used to produce forecasts of average 22 day ahead volatility. Forecasts are based on parameters estimated recursively from a rolling window of 1000 observations. This procedure results in 2460 22 day-ahead forecasts.

3.2 Economic information and forecast efficiency

In order to investigate if and how economic information enters volatility forecasts in general, and the VIX in particular, we will investigate a number of questions. *First*, is the current level of volatility related to the selected economic information? If this was not the case, one could not reasonably expect volatility forecasts to reflect any such information. *Second*, it will be tested whether volatility forecasts are related to economic information. This is a straightforward corollary to the first research question. Such a relation could merely be due to the fact that volatility forecasts use current and past volatility information.

The VIX has a conceptual advantage in that it may extract information from economic data that is relevant for future realisations of volatility, information not normally included in models for volatility. In order to examine this, two further hypotheses are tested. *Third*, it is established whether the predicted *changes* in the level of volatility (forecast – current level of volatility) is related to economic information. Only if this was the case could one reasonably argue that a volatility forecast allows for current economic information to drive its forecast beyond its effect on the current level of volatility. *Finally*, it will be tested whether the volatility forecasts are efficient, testing whether forecast errors made, are correlated with economic information available at the time the forecast was formed.

Two econometric tools will be used to test these hypotheses. First, following Fleming (1998) and Becker, Clements and White (2006), is the generalized method of moments (GMM) as it enables us to test whether a series $\varepsilon(y_t, x_t; \phi)$ (obtained after estimating a set of parameters ϕ) and a set of k_2 economic variables, q_t are orthogonal or not. Parameter estimates of ϕ are obtained by minimising

$$V = g(y_t, x_t, z_t; \phi)' H \, g(y_t, x_t, z_t; \phi), \tag{1}$$

where

[7] See Becker, Clements and White (2007) for exact specifications of these models.

$$g(y_t, x_t, z_t, \phi) = \frac{1}{T}\sum_{t=1}^{T} \varepsilon(y_t, x_t; \phi) z_t$$
$$= \frac{1}{T}\sum_{t=1}^{T} (y_t - x_t^{'}\phi) z_t \qquad (2)$$
$$z_t = \left(x_t^{'} q_t^{'}\right)^{'}$$

The definition of the scalar series y_t and the $(k_1 \times 1)$ vector x_t depend on the particular question at hand. The weighting matrix H is chosen to be the variance-covariance matrix of the moment conditions in $g(y_t, x_t, z_t; \phi)$, where allowance is made for residual correlation (see Hansen and Hodrick, 1980). In this context, the test for k_2 overidentifying restrictions (as z_t produces $k_1 + k_2$ moment conditions and ϕ is a $(k_1 \times 1)$ parameter vector to be estimated) is used to test the null hypothesis that $\varepsilon(y_t, x_t; \phi)$ and q_t are uncorrelated.

The second testing procedure is Harvey and Newbold (2000) generalization of Hotelling's test for a zero mean in a vector-valued random variable. In this paper's context the $(k_2 \times 1)$ random variable is $h_t = (\tilde{y}_t \otimes \tilde{q}_t)$. Variables with ~ are de-meaned and if y_t and q_t are uncorrelated then $E(\tilde{y}_t \otimes \tilde{q}_t) = 0$. The null hypothesis that y_t and every element in q_t are uncorrelated is tested using

$$MS = \frac{T - k_2}{k_2(T-1)} \bar{h} \hat{V}^{-1} \bar{h} \qquad (3)$$

where $\hat{V}$ is the sample variance covariance matrix of h_t as defined in Harvey and Newbold's (2000) allowing for autocorrelation due to the overlapping nature of the 22 day ahead forecasts. The calculated test statistic is compared against critical values coming of the $\mathrm{F}_{k_2, T-k_2}$ distribution.

The first three of the hypotheses posed above can be investigated with both methodologies. This is useful as there is only limited evidence on the empirical properties of the above testing procedures especially when using variance-covariance matrices which allow for autocorrelation of a relatively high order.

The *first* step is to investigate whether the economic information is related to the current level of volatility. If this was not the case, one would not expect a volatility forecast to incorporate such information. Here y_t is the prevailing level of volatility, x_t is a constant and q_t comprises the five economic variables *slope*, *cspr*, *oil*, *doil* and *twi*. As the volatility models utilise different proxies for volatility, the question of whether the choice of proxy, realized volatility, squared, or absolute daily returns, is crucial when evaluating this hypothesis. It is well known that the daily series of volatility proxies (in particular the squared and absolute daily returns) are noisy proxies of the latent volatility process, and hence it is examined whether these volatility proxies averaged over a number of days are correlated to the average of the selected economic variables over these days.

The *second* hypothesis to be tested is whether the volatility forecasts themselves are correlated with the selected economic information. For this purpose y_t is the volatility forecast, $y_t = f_{i,t}$, where $f_{i,t}$ is the volatility forecast of the *i*th model made at period *t* for the average volatility over the period *t*+1 to *t*+22, x_t is a constant and q_t remains $q_t = (slope_t, cspr_t, oil_t, doil_t)$.

Testing whether predicted volatility changes are correlated with economic information will reveal whether volatility forecasts do use economic data beyond its influence on the current level of volatility. For that purpose the *third* test sets y_t to $y_t = f_{i,t} - RV_t$, x_t is a constant and q_t is as before.

Lastly, it will be investigated whether the different forecasts are efficient with respect to the economic information available at the time the forecasts are formed. The GMM methodology will be used to estimate Mincer-Zarnowitz type regressions by setting $y_t = \overline{RV}_{t+1\rightarrow t+22}$, the average realized volatility over the next 22 business days, x_t is $x_t = (1\, f_{i,t})$ or $x_t = (1\, f_{i,t}^{MBF})$, where $f_{i,t}^{MBF}$ is a vector of all model based volatility forecasts and q_t is defined above.

3.3 Information Mapping

In order to examine the second potential difference between MBF and IV, we relate the different forecasts to past proxies of volatility. This will establish whether IV volatility forecasts are more flexible in the way they map past volatility information into volatility forecasts. This may explain why a) IV routinely outperform single model based volatility forecasts but b) a combination of model-based volatility forecasts appears to perform as well as the IV forecast.

The volatility proxies used here is the realized volatility RV_t. To compare the mappings of past volatility implied by the various forecasts it is necessary to use a flexible approach without assuming a specific functional form. In a related context Ghysels, Santa-Clara and Valkanov (2005, 2006) proposed the Mixed Data Sampling (MIDAS) approach. The MIDAS regression of the forecasts $f_{i,t}$ on past volatility proxies is achieved by estimating α, ϕ and $\theta = (\theta_1, \theta_2)$ in (exemplary for RV_t as volatility proxy)

$$f_{i,t} = \alpha + \phi \sum_{k=0}^{k\max} b(k,\theta)\, RV_{t-k} + \varepsilon_t\,, \tag{4}$$

where $b(k,\theta)$ is the weighting function applied to past volatility

$$b(k,\theta) = \frac{\beta\left(\frac{k}{k\max}, \theta_1, \theta_2\right)}{\sum_{j=1}^{k\max} \beta\left(\frac{j}{k\max}, \theta_1, \theta_2\right)} \tag{5}$$

$\beta(., \theta_1, \theta_2)$ is the Beta probability distribution and *kmax* is the maximum number of lags. The shape of the estimated weight functions may change across different subsample with such variation revealing a degree of flexibility in terms of mapping past volatility information into volatility forecasts.

4 Results

4.1 Economic Information

We first consider the results that reveal how economic information enters volatility forecasts and in particular whether the VIX does display any significant advantage compared to MBF.

INSERT TABLE 1 ABOUT HERE

From Table 1 we can see that the null hypothesis of orthogonality between the chosen economic variables and the current level of volatility as proxied by realized volatility, squared daily returns and absolute returns is clearly rejected by both the GMM test for overidentifying restrictions (GMM) and the Harvey-Newbold-Hotelling (HNH) test. This is true for daily observations but also for averages over longer time periods. Only for averages over 30 days do the rejections become marginal. This is likely the result of the test's reduced power when dealing with strongly overlapping data.

INSERT TABLE 2 ABOUT HERE

This result foreshadows the results shown in Table 2. Here it is demonstrated, again using the GMM and HNH test, that the volatility forecasts are significantly correlated with economic information not directly incorporated into the volatility models but available at the time the forecasts are formed. This result is not surprising given the clear correlation between the current level of volatility and the economic information. It is well known that volatility forecasts are driven by the current level of volatility.

Volatility forecasts, in particular those derived from volatility models, will depend on the estimated long-run mean for volatility and how quickly the volatility process is expected to revert to this level. Here we will investigate whether the change in volatility predicted by the various volatility forecasts, $f_{i,t} - RV_t$, is correlated to the selected economic information.

INSERT TABLE 3 ABOUT HERE

Table 3 displays the results of the test for overidentifying restrictions and the HNH test when $y_t = f_{i,t} - RV_t$, x_t is a constant and $q_t = (slope_t, cspr_t, oil_t, doil_t)$. Interestingly, the VIX does not produce forecasts which predict volatility changes that are correlated to economic information available at the time, *t*, at which the forecasts are formed. Predictably, most MBF display the same pattern. It is, however, interesting to note that *garrv* and *gjrrv* do behave differently as their predicted volatility changes are correlated to available economic information. The reason for this result is the nature in which RV_t enters the volatility model. RV_t enters the conditional volatility equation as an extra variable. If it wasn't included, the GARCH model would, as discussed above, estimate a long-run volatility and mean reversion to that long-run mean from the data, in particular the history of squared returns. When including RV_t into this model one allows non-smoothed current volatility to enter the volatility forecast. As it was established above, this current level of volatility is indeed related to the economic information available at time *t* and hence it is natural that the expected volatility change will be related to the economic information. The same effect can be seen for the *gjrrv* model.

This then raises the question why the *arma* and *arfima* models which are soley based on current and passed RV_t do not display the same pattern. In these models the history of current and past realized volatilities is used to extract information on the long-run average volatility and the speed of mean reversion from the data. RV_t does not serve to incorporate immediate volatility information into the model in the same way as it does for the *garrv* and the *gjrrv*. The *arma* and *arfima* models, therefore, do not produce forecasts of volatility changes that are related to economic information.

At this stage it is worth noting that this does not automatically imply that forecasts from the *garrv* and the *gjrrv* models are superior to that of VIX volatility forecasts. Here it is merely investigated how these forecasts are related to economic information.

INSERT TABLE 4 ABOUT HERE

Lastly, we will establish whether the forecasts are efficient with respect to the economic information available at time *t*. If a forecast is efficient with respect to a certain information set, its forecast errors should be uncorrelated with that information. Table 4 displays the results of the *J*-test for overidentifying restrictions which tests the null hypothesis that the forecast errors are indeed uncorrelated with the information in $q_t = \left(slope_t, cspr_t, oil_t, doil_t\right)$.

The results indicate that in general the volatility forecasts are efficient. Surprisingly, the VIX volatility forecast is the only one that exhibits a marginal rejection of this null hypothesis. Although at the level of rejection and taking into account the number of hypothesis tests undertaken here, not too much weight ought to be put on this single result.

In summarising the results so far, a number of interesting findings arise. All volatility forecasts reflect the selected economic information. Such information is reflected in the forecasts through their link to the current level of volatility. As such, that information seems of little value in terms of forecasting volatility beyond this relationship. As a consequence it appears as if volatility forecasts are indeed efficient with respect to the selected0 economic information, indicating that there is no scope for better use of that information in the context of forecasting volatility.

These results leave it open why the VIX is commonly found to be a superior volatility forecast compared to individual model based forecasts. An alternative explanation is investigated in the following Section.

4.2 Information Mapping

In the previous section it was impossible to establish that the apparent superiority of the VIX is due to its ability to incorporate information that is not directly represented in the majority of volatility models. The second conceptual advantageof implied volatility is that it is not a formal model that generates the volatility forecast. In contrast, demand and supply conditions in option markets produce this forecast.

This implies that the relationship between volatility forecasts and the available historic volatility information is unrestricted, and it may be such added flexibility that delivers the important advantage to implied volatility based forecasts. In other words, any model based volatility model may be too restrictive in how past volatility information is mapped into volatility forecasts. While it is not directly obvious how it could be *proven* that it is this conceptual difference that is responsible for the improved forecast accuracy of the VIX when compared against individual MBF, we will establish whether or not the relationship between VIX and past volatility proxies is significantly more flexible than that reflected in MBF.

The model in equations (4) and (5) is used to map volatility forecasts to volatility proxies available at the time of the forecast (*kmax* = 500). In order to evaluate whether this mapping changes through time, this estimation is done for rolling subsamples of length 1000 (2460 forecasts are available) with step size 50[8].

INSERT Figures 1 to 3 ABOUT HERE

In order to illustrate the findings the mappings for the four volatility forecasts, *vix*, *gar*, *garrv* and *arfima* are shown. The weight functions $b(k,\theta)$ are displayed in Figure 1 with the volatility proxy being RV_t[9]. For ease of exposition, only the weights for the first 50 (out of a maximum of 500) lags are displayed. Figure 1 reveals a

[8] The first subsample is for forecasts 1 to 1000, the second subsample for forecasts 51 to 1050, the third for 101 to 1100, etc.

[9] Qualitatively similar results are found when past squared or absolute daily returns are used.

number of interesting results.

In general the *vix* and *arfima* forecasts appears to put more weight on the distant volatility history. This is to be expected, as the *arfima* forecast is designed to capture long-memory in the volatility process, but it is interesting to see that the *vix* also appears to reflect this feature. The corollary of that is that the *gar* and *garrv* forecasts, on average, put more emphasis on the more recent information. The weight functions are almost exclusively monotonically decreasing. When mapping the past realized volatilities into the different volatility forecasts (Figure 3) *arfima*, *gar* and *garrv* display very little variation across the different subsamples. Interestingly, the *garrv* forecasts show very large weight on the very short lag realized volatilities, which without doubt, is a result of the inclusion of realized volatility as an additional explanatory variable into the GARCH volatility equation. Lastly, and most importantly for the conjecture evaluated here, the mappings of the *vix* forecasts display the largest amount of variation in their mappings. Thus appears as if the relative weight given by option markets to the immediate and the longer volatility history varies significantly through time. This variation, while present in all volatility models, is much more marked than in the MBF.

This finding lends support to the conjecture that forecasts derived from implied volatilities may be superior to MBF as they allow more flexibility in terms of how past volatility information is used. In particular option markets may decide from period to period, what amount of past information is relevant for the immediate (here 22 day ahead) future, whereas the MBF used here (and in all related studies) are estimated on the basis of a fixed estimation window length.

5 Concluding remarks

The behavior of option implied volatility and econometric model based forecasts has attracted a great deal of research attention. Much of this has focused on relative forecast accuracy and the informational efficiency of implied volatility. Generally, it has been found that implied volatility provides a more accurate volatility forecast relative to those generated from econometric models. A commonly held view is that this result is due to the fact that option implied volatilities capture a wider range of information than forecasts based on historical return data. An alternative conjecture is that the models used impose a certain amount of rigidity in the way in which the volatility history is used to produce volatility forecasts.

This paper demonstrated how both claims can be examined. In particular it was considered whether both implied volatility and model based forecasts reflect a set of economic information. The selected set of information relates to the term structure of interest rates and commodity prices. It was found that both implied volatility and model-based forecasts do subsume the selected set of economic information. It was further established that this information enters through its impact on the prevailing level of volatility and it is not apparent that this information enters VIX forecasts in any wider sense. Therefore it seems as though implied volatility does not use the selected economic information in a fundamentally different way than the model based volatility forecasts. The work presented here is, of course, not sufficient to conclude decisively that implied volatilities will never capture such information. It is possible that forecasts of such economic variables are indeed taken into account. As better time series forecasts become available, future research may show that implied volatilities do make use of that information.

Lastly, the analysis presented clearly demonstrates that the manner in which implied volatilities makes use of historical volatility information changes across. This clearly distinguishes implied volatility from model based volatility forecasts and may explain or at least contribute to explain why previous research has established that volatility forecasts implied from option markets appear to be superior to model based volatility forecasts.

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TABLE SECTION

	RV		r^2		$\|r\|$	
LAGS	*J*	*HNH*	*J*	*HNH*	*J*	*HNH*
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0005	0.0000	0.0000	0.0000
10	0.0006	0.0000	0.0010	0.0002	0.0000	0.0000
20	0.0205	0.0002	0.0197	0.0008	0.0035	0.0000
30	0.0593	0.0008	0.0560	0.0024	0.0218	0.0002

Table 1: Correlation between volatility proxies and economic information. *J*: p-value for the test for overidentifying restrictions in equations (1) and (2) with $y_t = RV_t, r_t^2 \; or \left|r_t\right|$, $x_t = 1$ and $q_t = \left(slope_t, cspr_t, oil_t, doil_t\right)$**.** For LAGS = 2, 5, 10, 20 and 30, y_t and q_t are the averages of the respective variables over LAGS periods. The variance-covariance matrix of the moment conditions, *H* in equation (1), allows for correlation of order (LAGS - 1). *HNH*: p-values of the Harvey-Newbold-Hotelling test with y_t and q_t defined as for GMM. The variance-covariance matrix $\hat{V}$ in equation (3), allows for correlation of order (LAGS - 1).

Forecast	*J-statistic*	*p-values (J)*	*HNH*
VIX	12.9047	0.0118	0.0001
gar	14.2806	0.0065	0.0000
gjr	17.9775	0.0012	0.0000
sv	25.5148	0.0000	0.0000
arma	22.0404	0.0002	0.0000
arfima	22.2658	0.0002	0.0000
garrv	19.3703	0.0007	0.0000
gjrrv	15.5696	0.0032	0.0002
svrv	23.9588	0.0001	0.0000

Table 2: Correlation between volatility forecasts and economic information. *J*: p-value of the test for overidentifying restrictions from equations (1) and (2) with $y_t = f_{i,t}$, $x_t = 1$ and $q_t = \left(slope_t, cspr_t, oil_t, doil_t\right)$**.** The variance-covariance matrix of the moment conditions, *H* in equation (1), allows for correlation of order 21. *HNH*: p-values of the Harvey-Newbold-Hotelling test with y_t and q_t defined as for *J*. The variance-covariance matrix $\hat{V}$ in equation (3), allows for correlation of order 21.

Forecast	*J-statistic*	*p-values (J)*	*HNH*
VIX	2.1094	0.7156	0.7046
gar	2.3294	0.6754	0.7917
gjr	3.6119	0.4611	0.5739
sv	4.6591	0.3241	0.5895
arma	7.9023	0.0952	0.1612
arfima	6.4934	0.1650	0.3290
garrv	13.8265	0.0079	0.0074
gjrrv	16.1470	0.0030	0.0027
svrv	9.8447	0.0431	0.3152

Table 3: Correlation between expected volatility changes and economic information. *J*: p-value of the test for overidentifying restrictions from equations (1) and (2) with $y_t = f_{i,t} - RV_t$, $x_t = 1$ and $q_t = \left(slope_t, cspr_t, oil_t, doil_t\right)$**.** The variance-covariance matrix of the moment conditions, *H* in equation (1), allows for correlation of order 21. *HNH*: p-values of the Harvey-Newbold-Hotelling test with y_t and q_t defined as for *J*. The variance-covariance matrix $\hat{V}$ in equation (3), allows for correlation of order 21.

Forecast Error	R^2	*p-values(J)*
VIX	0.7692	0.0373
gar	0.7273	0.3030
gjr	0.7087	0.2383
sv	0.7381	0.7863
arma	0.7724	0.2513
arfima	0.7678	0.3806
garrv	0.7599	0.2841
gjrrv	0.7582	0.2542
svrv	0.7632	0.2791
All MBF	0.7864	0.1219

Table 4: Forecast efficiency. R^2: R^2 of the Mincer-Zarnowitz regressions estimated from equations (1) and (2) with $y_t = \overline{RV}_{t+1\to t+22}$, $x_t = (1\, f_{i,t})$ or $x_t = (1\, f_{i,t}^{MBF})$, where $f_{i,t}^{MBF}$ is a vector of all model based volatility forecasts. $q_t = (slope_t, cspr_t, oil_t, doil_t)$. *p-values(J)*: p-value of the test for overidentifying restrictions from equations (1) and (2) with y_t, x_t and q_t as above. The variance-covariance matrix of the moment conditions, H in equation (1), allows for correlation of order 21.

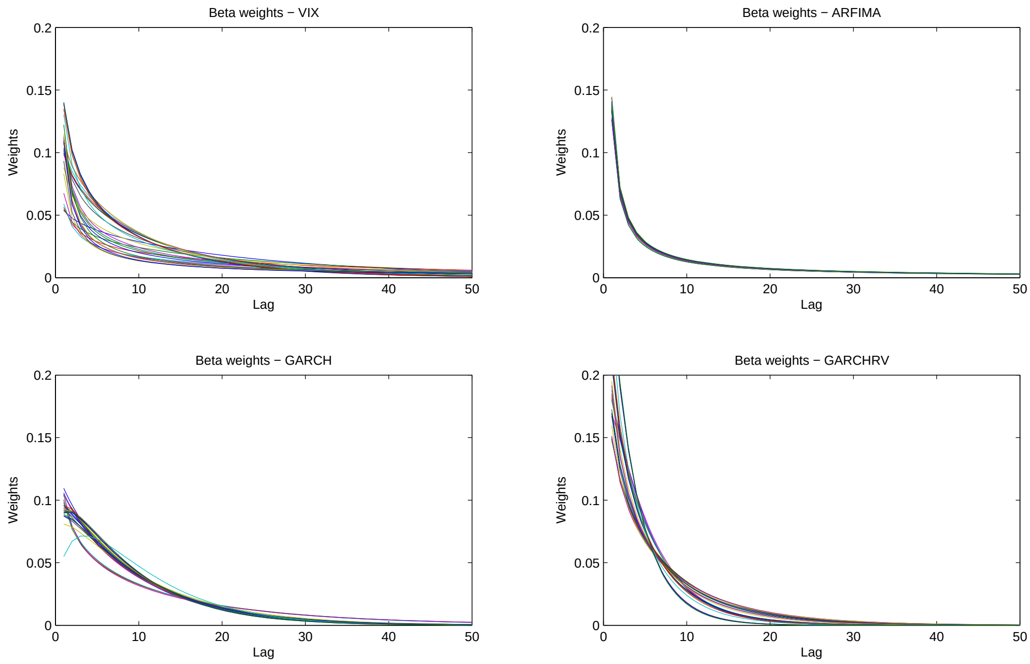

Figure 1: Information Mapping – Absolute Returns. Weight functions $b(k,\theta)$ (equation (5)) for VIX, ARFIMA, GARCH and GARCHRV volatility forecasts using daily realized volatility, RV_t, as volatility proxies.