The Value of Intraday Prices and Volume using Volatility-Based Trading Strategies

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Abstract

This paper investigates the role of intraday prices and volume to generate daily volatility forecasts used for individual stock trading. The analysis is based on a 7-year sample of transaction prices for 14 NYSE stocks. Volatility forecasts are obtained from daily returns in a GARCH equation which is augmented with several nonparametric intraday volatility measures or with volume. The overall results from various trading strategies suggest that the use of high frequency price data is not profitable. The baseline GARCH forecasts outperform the intraday price augmented GARCH forecasts. However, the information content in trading activity can enhance profits. The best performing strategies involve buying the stock when its forecasted volatility is extremely high, suggesting a stronger volatility-return relationship in turbulent periods.

Keywords: C53; C32; C14.

JEL Classification: Conditional variance; Trading rules; Intraday prices; Volatility signals, Directional change.

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1 Introduction

A vast body of literature investigates both long- and short-trading strategies based on the predictive power of past prices or returns, such as momentum investing strategies and technical analysis trading rules. Nevertheless, there is no reason why practitioners and investors should limit their focus to devising trading strategies based on prices or returns data, particularly as the evidence of their profitability over various time horizons is not consistent. Over the past decade there has been growing interest among academics and practitioners in modeling and forecasting the volatility of stock market returns. Volatility is a crucial concept for portfolio management, option pricing and financial market regulation, inter alios, but there are few studies that investigate whether volatility forecasts can lead to profitable trading. Continuous advances in volatility modelling could facilitate longer-lasting profitable trading as argued by Lasky (2001). In particular, although volatility and returns can have either positive or negative replationship depending on the market analysed, once the strength and the direction of this relationship is established, volatility forecasts can be exploited for profitable trading. For instance, it is well accepted in the US equity markets that very high levels of the VIX volatility index are associated with an increase in future returns of the S&P 500 index and vice versa.

A potential difficulty in modeling and forecasting volatility is that, in contrast with prices, the latent volatility process is unobserved even ex post so it needs to be proxied, but it has not been investigated in the literature which method of proxying will lead to most profitable trading. A well known fact in the forecasting literature is that if the squared daily returns are used as proxy for the "actual" daily variance, GARCH models do have very poor forecasting properties which may be taken to suggest that they are of limited practical use. A recent body of literature in financial econometrics establishes that it is possible to obtain better daily volatility forecasts by exploiting the information in intraday prices. In particular, large emphasis has been given to "realized" volatility approaches inspired by the earlier work of Schwert (1989) and popularized by Andersen and Bollerslev (1989). The "realized" volatility framework has the appealing feature of being nonparametric and so it enables quite precise measures of volatility without the need of making modeling assumptions.

This paper seeks to contribute to a novel but still sparse literature which introduces economic criteria in the analysis of volatility forecasts. Most extant studies are based purely on statistical criteria such as, for instance, the mean squared error and the goodness-of-fit of Mincer-Zarnowitz regressions. In particular, the question of how traders and investors can utilise volatility forecasts to devise trading strategies based on intraday price or volume information has not been investigated as yet and no evidence of profitability of such volatility-based trading of equities exists. The paper complements the literature also by investigating whether the additional use of intraday price or volume information helps to improve the profitability of trading strategies both on a risk-adjusted and cost-adjusted basis. For this purpose, it augments the baseline forecasting GARCH model with four competing "realized" volatility estimators based on intraday prices and with daily volume. The volatility forecasts are used as input signals for individual stock trading on the basis of various volatility-based trading strategies. As criteria to gauge the success of the volatility forecasts we use the standard risk-adjusted Sharpe ratio and alpha measures of perfomance. In addition, given that trading costs can substantially reduce profitability and that the various strategies and volatility forecasts imply different trading intensities, we provide performance measurement on a cost-adjusted basis as well. This paper presents the first evidence of the profitablity of volatility-based trading strategies using intraday price or volume information.

The sample spans 7 years of data over 02/01/97 to 31/12/03 for 14 large stocks traded on the NYSE and prices are recorded at 5-minute intervals. The degree of profitability of our trading strategies based on volatility forecasts vis-à-vis the passive buy-and-hold is economically plausible: the later is outperformed in about 65% of the stock-strategy cases under study on the basis of the standard Sharpe ratio and alphas, which falls to 35% when transaction costs are taken into account. Overall, the baseline GARCH forecasts based just on daily returns emerge as the most informative trading signals. The nonparametric intraday volatility measures that have been shown in previous studies to enhance daily GARCH forecasts from a statistical perspective do not appear so valuable when the objective is to trade on the volatility signals. Hence, the results reveal that the use of intraday price data to forecast daily volatility is not warranted from a trading perspective. In contrast, the information content of trading activity (daily volume) was found to enhance profits to some extent. The top performing strategies suggest buying the stock only when its volatility is extremely high indirectly supporting the notion that the volatility-return relationship is stronger in turbulent periods.

The rest of the paper is organized as follows. Section 2 provides a brief review of the relevant literature on volatility forecasts and their economic evaluation. Section 3 presents the nonparametric intraday volatility measures and the trading strategies devised. Section 4 discusses the empirical results and Section 5 concludes.

2 Background literature

Devising trading strategies that remain profitable after transaction costs is crucial for investors and asset managers. A vast body of literature focuses on the predictive ability of past returns used to derive, for instance, momentum and technical trading strategies. Since the seminal paper of DeBond and Thaler (1985, 1987) who identify negative serial correlation for winner and loser portfolios over periods of three to five years and Jegadeesh and Titman's (1993) study which documents momentum in the short- and medium-term, there has been a lot of evidence supporting momentum trading. For example, more recent studies such as Grundy and Martin (2001), Conrad and Kaul (1998), Daniel, Hirshleifer and Subrahmanyam, (1998) confirm the profitability of momentum trading and provide various behavioural explanations for the phenomenon. Likewise, technical analysis-based trading rules devised from past prices have been widely used to identify 'buy' and 'sell' signals for securities trading, as seen in Brock, Lakonishok and LeBaron (1992), Hudson, Dempsey and Keasey (1996) and Hatgioannides and Mesomeris (2007) among many others. It should be emphasized that the strategies implemented in the above studies exploit historical patterns in equity prices or returns.

However, comparatively less emphasis has been placed so far on the information content of volatility to predict future returns. There is limited research on trading strategies devised from volatility forecasts, although the literature suggests a positive or a negative (depending on the market analysed) relationship between volatility forecasts and returns (see, for instance, Balaban and Bayar, 2005). Recent work by Christoffersen and Diebold (2006) has revealed a direct connection between asset return volatility and the direction of price changes. This suggests that the pervasive volatility persistence in equity returns induces sign persistence which could be exploited to produce direction-of-change forecasts useful for market timing. Further, Kho (1996) suggests that excess returns generated by a moving-average-crossover technical trading strategy can be explained by the time varying risk premia and volatility.

Even though one can intuitively relate volatility forecasts to future returns, researchers have not explored how this relationship can be used to devise profitable trading strategies. Volatility models can indeed help practitioners to generate trading signals or enhance existing signals obtained from other trading indicators. Larsen (2004) argues that traders should resort to a variety of trading indicators to identify 'buy' and 'sell' signals, including the VIX volatility index.[1] Particularly, historical data indicate that when the VIX reaches low levels, say, below 13, markets tend to be at the top and a reversal is expected and when it reaches high levels, say, around 40, markets tend to be at their lowest level and are ready for an upward movement.[2] On this basis, Larsen suggests that VIX could be used as an oscillator to indicate the turning points in the market. In addition, Lasky (2001) favours the use of conditional variances obtained though GARCH modelling for predicting mean returns. He finds that large conditional variances for T-bonds in the period 1998-2001 are

[1] The VIX index, an implied volatility measure used as indicator of market sentiment, is listed on the Chicago Board Options Exchange. VIX is calculated using put and call option prices and it measures the market's expectations of 30-day volatility on the S&P 500 index. It is quoted continuously during US trading hours.

[2] See, for example, the discussion at 77Finance Ltd., the largest online financial directory in the UK at http://www.77finance.co.uk/volatility-index-trading-guide.html.

related to subsequent large drops in prices, while large conditional variances for 10 year T-notes are correlated with price increases but no relationship can be found with price decreases. Therefore, he emphasises that traders must establish first the relation between conditional variance and future market direction for each market.

Several studies have documented in-sample fit enhancement of GARCH models by including contemporaneous volume. However, lagged volume has been shown to bring no improvement in the accuracy of volatility forecasts.[3] With the increasing availability of high frequency data in the last decade the focus has shifted towards employing "realised" volatility approaches. *Realised variance* (RV) has been widely utilized for the prediction of FX return volatility and equity return volatility. For instance, using an equity price index and two currencies, Galbraith and Kisinbay (2002) find that 1-day-ahead forecasts from AR models fitted to RV outperform those from GARCH.

Other nonparametric intraday volatility estimators have been advocated in the recent literature as an alternative or complement to the popular RV measure. In the context of FX volatility prediction using 5-min DM/US$ returns, Ghysels et al. (2006) document that *realised power variation* (RPV) outperforms the more theoretically motivated RV. Using Yen/US$ and DM/US$ rates and the Spyder Exchange-Trade Fund that represents ownership in the S&P500 index, Liu and Maheu (2005) establish that RPV outperforms the *realized bipower variation* (RBP) in terms of improving the 1-day-ahead volatility forecasts. Fuertes, Izzeldin and Kalotychou (2009) compare the forecasts of GARCH models augmented with RV, RPV, RBP or *realized range* (RR) using a number of statistical criteria and tests. The additional use of intraday prices brings significant forecast accuracy gains relative to the baseline GARCH model and, in particular, RPV provides the most accurate 1-day-ahead GARCH forecasts.

Only a handful of studies focus explicitly on the economic role of "realized" measures of volatility. Fleming, Kirby and Ostdiek (2001) assess the importance of dynamically updating portfolio weights based on forecasts of the (co)variance matrix. Their results indicate that dynamic volatil-

[3] On the former, see, for instance, Bessembimber and Seguin (2003) and Kalotychou and Staikouras (2006). On the latter, see Brooks (1998), Donaldson and Kamstra (2009), Fuertes, Izzeldin and Kalotychou (2009).

ity timing strategies outperform passive strategies based on the efficient static portfolio with the same target expected return and volatility. In a sequel paper, Fleming, Kirby and Ostdiek (2003) show that using intraday returns to estimate the conditional covariance matrix can further improve portfolio performance. More specifically, their volatility timing strategies based on RV fare substantially better than other volatility timing and passive strategies. Using monthly returns and monthly RV (by aggregating daily squared returns) measures, Cakmakli and van Dijk (2007) illustrate the economic success of factor model forecasts by evaluating market and volatility timing trading strategies. They simulate an investor with a mean-variance utility function who faces an optimization problem (portfolio weight rebalancing) each period. Grané and Viega (2007) document that augmentation of GARCH models with a 5-min RV measure improves forecast ability which, in turn, leads to more accurate measures of minimum risk capital requirements.

3 Data and Methodology

Transaction prices and number-of-shares traded are obtained from Tick Data.[4] The observations pertain to 14 large stocks pertaining to the S&P500 which span the period 02/01/97 to 31/12/03, a total of 1761 days. Stocks were chosen in order to have wide market coverage in terms of market capitalization and sector representation. The stocks are American Express (AXP), AT&T (ATT), Boeing (BA), Caterpillar (CAT), DELL, General Electric (GE), General Motors (GM), IBM, JP Morgan (JP), KO (Coca-Cola), McDonald (MCD), Microsoft (MSFT), Procter & Gamble (PG) and WAL-MART (WMT). Among these, AXP and JP are financials; BA, CAT, GE, GM are industrials; MSFT, DELL, IBM are technology; PG, WMT, KO, MCD are food supply chains, and AT&T is telecommunication. Different sectors exhibit various degrees of liquidity and volatility, for instance, technology stocks tend to be more active than industrial ones. Therefore, it is important to see if the results are robust to various liquidity/volatility conditions. Daily observations on the S&P500 price index and the US 3-month Treasure Bill yield are obtained from Datastream.

[4] *www.tickdata.com* provides high frequency data on a commercial basis for equity and commodity markets.

3.1 Volatility forecasting framework

In order to construct intraday volatility measures the trading day [9:30am-4:00pm] is divided into M intervals of 5-minute length. The price at the start of the jth intraday interval is computed as the average of the closing and opening prices of intervals $j-1$ and j, respectively. The jth intraday return (on day t) is therefore computed as

$$r_{t,j} = 100\left(\frac{\log(p^c_{t,j}) + \log(p^o_{t,j+1})}{2} - \frac{\log(p^c_{t,j-1}) + \log(p^o_{t,j})}{2}\right), j = 2, ..., M-1 \tag{1}$$

where $p^c_{t,j}$ ($p^o_{t,j}$) is the closing (opening) price of the jth intraday interval. Typically, we have $M =$ 78 intraday returns and one overnight return, with the exception of days with delayed openings and/or early closings of the NYSE. Overnight returns are not accounted for because the weight such a return should deserve is somewhat arbitrary as Hansen and Lunde (2006b) and Engle et al. (2006) argue. The intraday returns are aggregated into daily returns, $r_t = \sum_{j=1}^{M} r_{t,j} = \log(\frac{p^c_{t,M}}{p^o_{t,1}})$, to which the following ARMA(p,q) - GARCH(r,s) model is fitted

$$r_t = \theta_0 + \sum_{i=1}^{p}\theta_i r_{t-i} + \sum_{j=1}^{q}\lambda_j u_{t-j} + u_t, u_t|\mathcal{F}_{t-1} \sim iid(0, h_t) \tag{2a}$$

$$h_t = \omega + \sum_{i=1}^{r}\alpha_i u^2_{t-1} + \sum_{j=1}^{s}\beta_j h_{t-j} \tag{2b}$$

where u^2_t are the squared whitened returns.[5] The lag orders (p, q) and (r, s) are chosen so as to capture all the serial dependence in returns and the volatility clustering, respectively. The ARMA-GARCH is then augmented with a nonparametric volatility estimator or proxy (v_{t-1}) as

$$h_t = \omega + \sum_{i=1}^{r}\alpha_i u^2_{t-1} + \sum_{j=1}^{s}\beta_j h_{t-j} + \gamma v_{t-1} \tag{3}$$

using as candidates for v_{t-1} the realised variance (RV), realised range (RR), realised power variation (RPV), realised bipower variation (RBP) or trading volume (VOL). The *realised variance,*

[5] We do not consider an asymmetric GARCH because the asymmetric relation between positive versus negative price movements and volatility (e.g. rationalized as 'leverage effect') has been shown to be rather weak or absent in individual stock price series as compared to broad stock price index series (see, for instance, Tauchen et al., 1996).

computed as the sum of intraday returns

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2, \quad t = 1, 2, ..., T \tag{4}$$

is the most theoretically motivated (Andersen and Bollerslev, 1998; Andersen et al., 2001).

The *realised range* estimator introduced by Christensen and Podolskij (2005), a generalization of the range estimator of Parkinson (1980), is defined as

$$RR_t = \frac{1}{4\log 2}\left[\sum_{j=1}^{M} 100 \times \left(\log(p_{t,j}^h) - \log(p_{t,j}^l)\right)^2\right] \quad t = 1, 2, ..., T \tag{5}$$

where $\log(p_{t,j}^h)$ and $\log(\log p_{t,j}^l)$ are the high and low prices of the jth interval, and the scaling factor $4\log 2$ is a bias-correction for market microstructure effects. BN-S (2002a) and Christensen and Podolskij (2005) show that, in the absence of market frictions (bid-ask bounce, infrequent trading, price discreteness), the RR estimator is more efficient than other variance estimators based on squared returns. But this is not so in more realistic setups (Martens and van Dijk, 2006).

Another estimator introduced by Barndoff-Nielsen and Shephard (2004; BN-S), the *realised power variation* of order z, is

$$RPV_t(z) = \mu_z^{-1}\delta^{1-z/2}\sum_{j=1}^{M} |r_{t,j}|^z, \ 0 < z < 2, \quad t = 1, 2, ..., T \tag{6}$$

where

$$\mu_z = E\,|\mu|^z = 2^{z/2}\frac{\Gamma(\frac{1}{2}(z+1)}{\Gamma(\frac{1}{2})}, \ \mu \sim N(0,1)$$

which for $z = 1$ becomes the realised absolute variation. Liu and Maheu (2005) study the 1-day-ahead forecasting properties of (6) for different orders z and find that $0.5, 1$, and 1.5 yield the lowest RMSE. Absolute returns are more persistent than squared returns so RPV could outperform RV in forecasting financial risk. Also RPV is robust to jumps in the price process and thus may lead to better predictions than RV when the sample period contains large jumps. Further discussion can be found in Ghysels et al. (2006) and Forsberg and Ghysels (2007). In a similar fashion, BN-S (2004) define the *realised bipower variation* estimator as

$$RBP_t = \mu_1^{-2}\sum_{j=2}^{M} |r_{t,j}|\,|r_{t,j-1}| \tag{7}$$

where $\mu_1 = E(|\mu|) = \sqrt{2}/\sqrt{\pi} \simeq 0.79788$ and $\mu \sim N(0,1)$. BN-S (2004) show that RBP converges in probability to the integrated variance and so it is also immune to jumps.

The asymptotic properties of these intraday volatility estimators have been derived under ideal conditions such as no market microstructure noise. Unfortunately, in realistic settings the influence of bid-ask bounce (Ross, 1984), screen fighting (Zhou, 1996), price discreteness and irregular trading can, at very high frequencies, render these intraday volatility estimators biased. The 5-minute sampling interval has been shown to be small enough to accurately capture price dynamics and large enough to dampen down the adverse effects of market microstructure frictions.[6] For completeness, the daily trading volume (VOL) defined as the total number of shares traded is also used as GARCH augmentation variable.

The sample is divided into an estimation period ($T_0 = T - T_1$) of fixed length 1261 days, and a holdout or evaluation period (T_1) of 500 days. Hence, each model is estimated over an initial window, denoted $[1, t]$, and a 1-day-ahead ex post volatility forecast is generated. The window is rolled forward, $[2, t+1]$, to obtain a second forecast and so forth over 500 iterations.

3.2 Volatility-Based Trading Strategies

At the end of day T_0 we generate a one-day-ahead volatility forecast and, on this basis, we deploy several long-only, short-only and long-short trading strategies that can be feasible for practitioners. This approach is rolled forward 500 times. Thus our trading simulaton spans the 500-day out-of-sample period. Each of the aforementioned GARCH models is used separately to generate volatility signals. The trading strategies are deployed individually for each of the 14 stocks.

Following Lasky's (2001) analysis, we start by identifying the nature of the return-volatility nexus in order to map the volatility forecasts into 'buy' and 'sell' signals. For this purpose, a contemporaneous regression of daily stock returns r_t on volatility σ_t^2 is fitted over the estimation

[6] ABDE (2001), BN-S (2002a,b), and Taylor and Xu (1997), inter alios, advocate this grid also because daily returns standardized by 5-min realised volatility are approximately normal. In the forecasting literature, studies that use 1-, 5-, 15- and 30-min data report mixed results but overall they also tend to favour the 5-min sampling (Martens and van Dijk, 2006; Pong et al., 2004; Ghysels et al., 2006; Galbraith and Kisinbay, 2002).

window ($T_0 = 1261$ days) and the sign of the slope coefficient is analysed. For this purpose, the 'observed' daily volatility is proxied by the sum of 5-min squared intraday returns (denoted $\tilde{\sigma}_t^2$).[7] Volatility forecasts for day $t+1$ are obtained from daily open-to-close returns (baseline GARCH model) or from intra-daily prices (each of the five augmented GARCH models) as indicated above. For each stock, the sign of the return-volatility relation in conjunction with the day $t+1$ volatility forecast will be translated into a trading signal for day $t+1$.

3.2.1 Long-Only Volatility Strategies

The contemporaneous regression of daily returns on their volatility over the estimation period ($T_0 = 1261$ days) clearly suggests that the overall relationship between returns and volatility across our 14 stocks is positive.[8] This implies that if volatility on day $t+1$ is expected, say, to increase then this signals a rise in the stock return.

Let us denote by h_{t+1}^m the volatility forecast for day $t+1$ generated with information up to day t using model m. The first volatility-based strategy, called Directional, seeks to exploit the predictive ability of the models in terms of directional change in the volatility level. Accordingly, if the volatility forecasted for $t+1$ represents an increase in volatility with respect to the 'observed' or realized volatility on day t (i.e. $h_{t+1}^m - \tilde{\sigma}_t^2 > 0$), this amounts to a buy signal for day $t+1$; so we buy the stock at the opening price on day $t+1$. Next we derive the trading signal associated with the forecast for day $t+2$ and so forth. If two (or more) consecutive buy signals are generated, this amounts simply to buying and holding the stock after the first buy signal. Thus the stock will be held for, say, s days until a sell or volatility drop signal is generated for day $t+s+1$ on the basis of information up to day $t+s$ (i.e. $h_{t+s+1}^m - \tilde{\sigma}_{t+s}^2 < 0$); so the stock will be sold at the opening price on day $t+s+1$.

A potential problem with this simple Directional strategy is very frequent trading (i.e., a large

[7] Alternatively employing the realised range, realised power variation or realized bipower variation for these regressions produces identical results on the sign of the return-volatility relation. This is unsurprising given the high correlation between the four realised volatility measures (Fuertes, Izzeldin and Kalotychou, 2009).

[8] The results of these regressions are available from the authors upon request.

number of buy/sell signals some of which may be too noisy) thus incurring large transaction costs. Evidence from Lee et al. (2003) and Corrado and Lee (1992) suggests that technical analysis trading indicators can complement existing market timing strategies. Therefore, we deploy a second strategy which adds a Simple Moving Average (SMA) and a Double Crossover Moving Average (DCMA) as an 'overlay' to the Directional strategy in order to: i) eliminate false signals and reduce unnecessary trading (achieved by the combined use of both SMA and DCMA), and ii) limit the potential losses caused by large price falls (achieved by DCMA). SMA is commonly used for generating trading signals as carried out, for instance, in Brock et al. (1992) while DCMA is additionally applied as stop-loss rule to confirm the change in the price trend. In practice, the choice of a stop-loss rule is subjective and it depends on traders' experience and personal preferences: we adopt a 5-day SMA and a 5-day/20-day DCMA approach.[9] In particular, in this long-only Directional SMA-DCMA strategy, a buy signal on day $t+1$ is generated if: 1) the forecasted variance on day $t+1$ is greater than the realized variance on t as in the baseline Directional strategy, 2) the opening price on day $t+1$ is greater than the SMA_{t+1} signal, and 3) the $DCMA_{t+1}$ signal does not indicate to stop trading. If the three conditions are met, we buy the stock at the opening price on day $t+1$.

Our third strategy, called Top 20% Volatility (Top20, hereafter), exploits the magnitude of the volatility forecast instead of the directional-change forecast. This is a long-only strategy based on the notion that the degree of association between volatility and returns is stronger when volatility is extremely high (Lasky, 2001). In this case, the volatility sequence observed during the in-sample-period $\{\tilde{\sigma}_t^2\}_{t=1}^{T_0}$ is ranked in ascending order to identify the 80th percentile or top 20% cutoff point, denoted κ_{80}, beyond which volatility is regarded as extremely high.[10] Over the in-sample period, the top 20% cutoff volatility has an average of 6.15% across stocks and range $[4\%, 13\%]$ with

[9] This is one of the commonly used day-spans for short trading cycles as seen in Pring (2002). The 5-day SMA is created as the simple moving average of day $t-1$ to $t-5$ closing prices, $SMA_t = \frac{P_{t-5}+P_{t-4}+\ldots+P_{t-1}}{5}$. The 5-day/20-day DCMA combines a short term (5-day) and a long term (20-day) SMA: if short-term SMA falls below the longer term SMA, then a sell signal (i.e. the stop-loss signal) is generated, which triggers termination in trading.

[10] The 10% cut-off was also considered but was found to be too extreme since virtually no signals were generated.

the minimum and maximum levels exhibited by GM and DELL, respectively. DELL (technology sector) is the most volatile stock in our sample with an in-sample period average realised variance of 9.58%, whereas GM (industrial) is one of the least volatile stocks with 2.95% period average variance. In line with the notion of time-varying risk, for each stock we recursively update the volatility cutoff by rolling the initial 1261-day length window forward to generate a series of cutoff points, $\{\kappa_{80,t}\}_{t=1}^{500}$, one for each day in the holdout period. If the volatility forecasted for $t+1$ is large ($h_{t+1}^m > \kappa_{80,t}$), this amounts to a buy signal so we buy the stock at the opening price on day $t+1$. Next, we assess the trading signal associated with the out-of-sample volatility forecast h_{t+2}^m and cutoff $\kappa_{80,t+1}$, and so forth. The stock will be held until a sell signal (medium or low volatility) is generated, say, for day $t+s$ (i.e. $h_{t+s}^m < \kappa_{80,t+s-1}$); so the stock will be sold at the opening price of day $t+s$.

3.2.2 Short-Only Volatility Strategy

Our fourth trading approach is the Bottom 20% Volatility (Bottom20, hereafter) strategy, a short only strategy where we short-sell the stock if its volatility falls below a pre-determined cutoff point $\kappa_{20,t}$. Accordingly, this strategy builds upon the notion that the association between volatility and returns is stronger for extremely low volatilities (Lasky, 2001). Therefore, through a rolling window (fixed length=1261 days) of realized volatilities we obtain the sequence of 20th percentile cutoffs for each stock $\{\kappa_{20,t}\}_{t=1}^{500}$. A sell signal is obtained for day $t+1$ if the forecasted volatility is low, $h_{t+1}^m < \kappa_{20,t}$, and so we sell the stock at the opening price of day $t+1$. We unwind the trade at the opening price of day $t+s$ when a buy signal is generated, $h_{t+s}^m > \kappa_{20,t+s-1}$. Over the in-sample period, the bottom 20% cutoff volatility has an average of 2.03% across stocks and range $[1\%, 4\%]$ with the minimum and maximum levels exhibited again by GM and DELL, respectively. No SMA or DCMA rules are overlaid in the Top20 and Bottom20 strategies because these strategies are expected to generate fewer trading signals (less noisy) than the Directional strategy and thus will not incur high transaction costs. The trading intensity associated with each strategy and volatility forecating model is illustrated below in Section 4.

3.2.3 Long-Short Volatility Strategy

The long-short strategy is simply a combination of the Top20 long-only strategy and the Bottom20 short-only strategy. This is a typical example of a market timing strategy, where one opportunistically goes long or short (short-sells) an individual equity. there has been increasing interest in long-short strategies since the 1990s and the emergence of hedge funds. Evidence from the hedge fund industry indicates that when long and short investment strategies are implemented on a portfolio of stocks simultaneously, they could enable investors to generate high absolute returns.[11] Given that the UK and US regulatory frameworks limit short-selling in mutual funds and traditional asset management firms, the strategy we suggest in this section would be feasible for hedge fund managers. One potential problem of such a long-short strategy may be high transaction costs due to frequent trading in a portfolio.

3.2.4 General Trading Considerations

No Trading Signal. In reality, if no trading signal is obtained, it is unlikely that the trader will keep the cash in a non-interest bearing account. Therefore, suppose that for the long-only strategy a buy signal is generated on day t and a sell signal is generated on day $t+s$; if no further buy signal is generated from day $t+s$ onwards we assume that the investor places the money in the risk-free asset. Likewise, the returns on days where we do not get a sell signal in the short-only strategies, or neither a buy nor a sell signal in the long-short strategies, are the risk-free asset returns. The latter are proxied by the daily values of the US 3-month Treasury Bill.

Assessing the Profitability of Trading. Our analysis implies a total of 70 competitions or horseraces resulting from the pairwise combination of 5 volatility-based trading strategies and 14 stocks. In each horserace the contest is between six volatility forecasting models. These include a baseline GARCH based on daily returns, four augmented versions that incorporate intraday price

[11] Absolute returns are defined as the returns an asset or a portfolio earns irrespective of the benchmark.

information in different ways (GARCH-RV, GARCH-RR, GARCH-RPV and GARCH-RBP) and another augmented GARCH model which incorporates trading volume information.

For each strategy-stock pair, the main question is whether an active volatility-based stock trading strategy outperforms the corresponding buy-and-hold individual stock (B&H) strategy and, relatedly, which of the volatility forecasting models is more effective in this sense. Two standard profitability criteria are used for this purpose. First, the incremental Sharpe ratio (ΔSR) is used to rank the competing forecasts in terms of excess annualized return per unit of overall risk. ΔSR is defined as the SR of the trading strategies over-and-above that from the B&H strategy. Second, the incremental Jensen's alpha ($\Delta\alpha$) is employed to compare the forecasts in terms of the excess return they yield over the security's theoretical expected return. $\Delta\alpha$ is defined as the annualized alpha of the strategy over-and-above the annualized alpha of the passive B&H.

Finally, we bring transaction costs into the picture which is important because all our strategies involve daily trading and a large number of buy or sell signals is expected for some strategies (e.g. Directional). Those where one should expect to generate less trading signals are the Top20 and Bottom20 strategies because they only involve trading following extreme volatility levels. The average level of implicit transaction costs for a US institutional investor trading large stocks is between 25 and 31 basis points (bp) per trade.[12] Thus we also compute the cost-adjusted ΔSR and $\Delta\alpha$ calculated on the basis of daily returns net of transaction costs.

4 Empirical Results

4.1 Preliminary Comparison: Statistical Criteria

Table 1 shows the distributional properties of five measures of daily volatility — squared returns, realised variance, realised range, realised power variation, realised bipower variation — and trading volume. All measures show positive skewness and large kurtosis with squared returns having the

[12] The 25bp and 31bp figures used in this paper are based on the implicit traded costs estimated for large-cap stocks in the studies, respectively, by Peterson and Sirri (2003) for NYSE stocks and Bessembinder (2003) for Nasdaq and NYSE stocks. These estimates have been confirmed as reasonable in informal talks with practitioners at Baring Asset Managment.

largest kurtosis.

[Table 1 around here]

By using mean volume as a proxy for trading activity, stocks can be ranked from more to less active as: MSFT, DELL, GE, IBM, JPM, WMT, AXP, MCD, KO, BA, GM, PG, ATT and CAT. The RV and RBP volatility measures have approximately the same mean. The mean of RR is generally smaller than that of RV with the exception of the two most traded stocks. The mean of RPV(for $z = 1.5$) is slightly higher than the mean of the other intraday-estimated volatility measures. But RPV is not in the same units as the other three volatility measures, so any comparison of their moments has to be interpreted with caution.[13] Relative to the mean, the RPV and volume measures have generally the lowest dispersion (StDev/Mean) which suggests that they are the least noisy in the present context followed by RR. At the other extreme, the crude squared return has a StDev/Mean ratio about five times larger than RPV.

Let σ_t^2 denote the population measure of volatility, which in the present context is the *conditional variance,* and its proxy ($\tilde{\sigma}_t^2$) for forecast evaluation is the sum of 5-min squared returns. The accuracy of model m forecasts, $\{h_{t,m}\}_{t=1}^{T_1}$, is gauged through the following statistical loss functions widely used in the forecasting literature:

[13] We follow Fuertes et al. (2009) in choosing order $z = 1.5$ for RPV. Building on the results in Liu and Maheu (2005), they compare RPV(0.5), RPV(1) and RPV(1.5) according to their distributional properties, in-sample model-fit and out-of-sample forecasting properties. Firstly, daily returns standardized by RPV ($z = 0.5$) become normal at the 10%, 5% or 1% level in none of the stocks, 7 stocks ($z = 1$), and 9 stocks ($z = 1.5$). Second, the model fit of GARCH-RPV is clearly superior, according to the loglikelihood, AIC and SBC, for $z = 1.5$ also. Third, for the majority of stocks according to virtually all loss functions considered, the forecast errors of GARCH-RPV are smaller for $z = 1.5$.

Mean absolute error	$MAE = \frac{1}{T_1}\sum_{t=1}^{T_1}\left|\tilde{\sigma}_t^2 - h_{t,m}\right|$
Mean squared error	$MSE = \frac{1}{T_1}\sum_{t=1}^{T_1}(\tilde{\sigma}_t^2 - h_{t,m})^2$
Heteroskedasticity-adjusted MSE	$HMSE = \frac{1}{T_1}\sum_{t=1}^{T_1}(1 - \tilde{\sigma}_t^{-2}h_{t,m})^2$
Adjusted mean absolute percentage error	$AMAPE = \frac{1}{T_1}\sum_{t=1}^{T_1}\left|\frac{\tilde{\sigma}_t^2 - h_{t,m}}{\tilde{\sigma}_t^2 + h_{t,m}}\right|$
Mean mixed error (U)	$MME(U) = \frac{1}{\#U}\sum I_U \cdot e_{t,m}^2 + \frac{1}{\#O}\sum I_O \cdot \lvert e_{t,m}\rvert$
Mean mixed error (O)	$MME(O) = \frac{1}{\#U}\sum I_U \cdot \lvert e_{t,m}\rvert + \frac{1}{\#O}\sum I_O \cdot e_{t,m}^2$
Gaussian maximum likelihood error	$GMLE = \frac{1}{T_1}\sum_{t=1}^{T_1}\left(\ln h_{t,m} + \tilde{\sigma}_t^2 h_{t,m}^{-1}\right)$

In the MME(U) and MME(O) criteria, $e_{t,m} = \tilde{\sigma}_t^2 - h_{t,m}$ denotes the forecast error for model m. $\#U$ is the number of underpredictions and $I_U = 1$ if $e_{t,m} < 0$; likewise for $\#O$ and I_O.

In addition, we also utilize the R^2 of Mincer-Zarnowitz level regressions (MZ-R^2), also called unbiasedness-regressions in the literature, a measure of the informational content of the volatility forecasts.[14] Table 2 presents in Panel A these statistical criteria for two representative stocks, American Express (AXP) and IBM. Bold indicates the best augmented model and the last row (Benefit %) reports the improvement that it brings versus GARCH.

[Table 2 around here]

The results for AXP and IBM illustrate that, nearly invariably across loss functions, the GARCH-RPV forecasts emerge as the most accurate.[15] This is in line with extant studies which illustrate that, not only intraday information appears worthwhile but RPV outperforms RV, RR and RBP (Liu and Maheu, 2005; Ghysels et al., 2006). Panel B provides the frequency (across stocks) with which a given forecasting model wins the race. A unanimous result across loss functions also in line with the literature on daily volatility forecasting is that the GARCH and GARCH-VOL approaches are relatively poor: for none of the stocks do these models win the race. These results are consistent with the recent literature which suggests on the basis of statistical criteria that by exploiting intraday prices one can improve the accuracy of daily volatility forecasts. In the next sections we revisit this question on the basis of profitability criteria.

[14] The MZ levels regression is $\tilde{\sigma}_t^2 = a + bh_{t,m} + e_t, t = 1, ..., T_1$. Hence, h_t will be unbiased for the true variance σ_t^2 if $a = 0$, $b = 1$ and $E(e_t) = 0$. The R^2 from this regression (called MZ-R^2) reflects the variance but not the bias-squared component of MSE, that is, it corrects for bias.

[15] The results for all 14 stocks are available from the authors upon request. For a detailed discussion of the statistical comparison of forecasts from GARCH and augmented GARCH models based on the same sample see Fuertes et al. (2009).

4.2 Performance Evaluation and Risk Management

Table 3 presents summary statistics for the volatility timing strategies. It reports the wealth or end-of-period value (EPV) generated by investing \$100 over a 500-day trading period from 08/01/2002 to 31/12/2003 relative to the EPV of the buy-and-hold for the corresponding stock.[16] Alongside the incremental EPV, the table reports the annualized returns and standard deviation and the number of trading signals.

[Table 3 around here]

It is evident from the table that the highest annualised return accross the board is generated by the Top20 strategy, which buys the stock when the forecasted volatility is too high, and it is closely followed by the Long-Short Strategy which longs or shorts the stock when the volatility, respectively, jumps too high or drops too low. One would expect that the highest return strategy is ultimately the riskiest one, however, our results show otherwise: the Top20 strategy is a medium risk strategy, being less volatile than the Directional or Long-Short strategy across all stocks and all forecating models[17]. The least risky strategy appears to be the one that involves only shorting the stock, Bottom20, albeit generating dissapointing rewards, both in terms of returns and EPVs. This indirectly suggests that the contention that the return-volatility link is strongest when volatility levels are extreme is more pertinent for large (as compared to low) levels of volatility. The Long-Short strategy EPVs, annualised returns and standard deviations are largely driven by the Top20 rather than the Bottom20 strategy because the latter involves comparatively few trades over the period, making its contribution to the performance of the long-short strategy small. The large number of trades affects the standard deviation of the Directional strategy, the most riskiest one. However, once the DCMA stop-loss is introduced to reduce excessive (noise) trading, the risk is

[16] For example, $Wealth_t = Wealth_{t-1} \times (1 + r_t)$, where r_t is the return generated by the strategy in question on day t .

[17] The average annualised return and standard deviation of S&P 500 index in the same period are 1.83% and 22.11% respectively, while the annualised average risk free return is 1.31%. This implies that the Top20 strategy gives us, on average accross stocks, higher returns than both the index and risk free investment and lower risk than the index.

more than halved in many cases.

We now turn to the question of whether intraday prices and volume add any economic value to the GARCH forecasts that are based just on daily returns and whether they increase the riskiness of our trading strategies. EPVs and annualised returns imply that intraday prices do not add value to investors but volume does. For example, the trading using GARCH-VOL forecasts generates highest annualised returns in 40 out of 70 stock-strategy combinations, in spite of not always having the highest risk. In particular, the model generating the highest risk (in 32 out of 70 cases) is GARCH-RR, followed by GARCH-VOL with the highest standard deviation in 21 out of 70 cases. Note that the figures in Table 3 do not take into account the impact of risk or cost of trading on EPVs or annualised returns, so they should be trated only as indicators of performance.

To account for risk, we compute the reward-to-risk (Sharpe ratios, SR hereafter) and alphas of the volatility-based trading strategies and the passive B&H. However, in the present analysis which focuses on individual stock trading, a larger weight should be given to the Sharpe ratio that adjusts for total risk as opposed to the alpha measure which focuses on systematic risk. The SRs and alphas are reported in Table 4.

[Table 4 around here]

The Sharpe ratios indicate that the returns of the volatility-based trading strategies more than compensate for their total risk in over two thirds of the cases (50/70). For those outperforming cases ($\Delta SR > 0$), the Sharpe ratio of each strategy using the best forecasts is averaged across stocks giving 0.64 for the Top20 strategy (GARCH forecasts), 0.40 for the Long-Short strategy (GARCH), 0.20 for Directional (GARCH-VOL), -0.34 for Dir SMA-DCMA (GARCH-RV), and -0.34 for Bottom20 (GARCH-VOL).

The incremental annualized alphas vis-à-vis the B&H alphas are reported in Table 4. Thus in each of the 70 competitions the winner forecasting model (signified in bold) is the model that delivers the largest $\Delta\alpha > 0$.The annualized alpha of the B&H benchmark averages 2.76% across stocks.

For the strategies, listed from best to worse, the average alpha is 5.44% (Top20 strategy), 2.34% (Long-short), 1.38% (Directional), -0.93% (Direct SMA-DCMA) and -3.06 (Bottom20) where the averaging includes all 14 stocks and all 6 forecasting models. At individual stock level, the leading Top20 strategy is able to beat the B&H strategy ($\Delta\alpha > 0$) for 8 stocks. A closer look at those 8 stocks reveals that the best volatility signals (largest $\Delta\alpha > 0$ across forecasting models) come from the simple GARCH in 4 stocks, GARCH-VOL in 2 stocks, GARCH-RR in 1 stock and GARCH-RBP in the remaining stock. Thus the GARCH forecasts emerge more frequently (across stocks) as the most effective volatility-based trading signals. Overall, considering the 70 competitions (14 stocks $\times$ 5 strategies) there is a total of 40 instances where the B&H alpha is improved upon. Among these 40 cases, the largest alphas and, in turn, the largest improvement in profitability over the B&H given by $\Delta\alpha$, are 40.24% with the Long-Short strategy (GARCH-VOL signals for stock ATT), 38.23% with the Top20 strategy (GARCH for stock ATT), 36.77% with the Directional strategy (GARCH-VOL for stock CAT), 26.28% with the Dir SMA-DCMA strategy (GARCH-RR for GM) and 7.73% with the Bottom20 strategy (GARCH for WMT).

Thus the overall picture from the alphas suggests, first, that volatility-based trading strategies for individual stocks can deliver larger excess returns than buying and holding the individual stock. Second, augmenting GARCH models with lagged volatility measures based on intraday prices is not warranted for volatility-based trading strategies. Third, the volatility signals from GARCH models augmented with lagged trading volume are comparable (or, in some cases, superior) to the GARCH forecasts in terms of volatility-based trading profitability. Fourth, the GARCH-RPV forecasts lead to relatively inferior profitability. These findings are interesting since they are at odds with the evidence from purely statistical comparisons; the overwhelming evidence of which suggests that lagged volume does not help in predicting future volatility and that RPV is a relatively good forecaster (see, for instance, Fuertes, Kalotychou and Izzeldin, 2009; Donaldson and Kamstra, 2004).

4.3 Transaction Costs

It is important to bring transaction costs into account in the present empirical analysis for three simple reasons. First, the five volatility-based trading strategies under study imply a different frequency of trading by construction. Second, the six competing models used to produce volatility forecasts (that trigger the trading) may also result in a different number of trading signals ceteris paribus. Third, a fair comparison of active strategies with the passive B&H strategy needs to take into account the presence of transaction costs in the former. For this purpose, we recalculate the EPVs, Sharpe ratios and Alphas using daily returns net of transaction costs. Transaction costs of 28bp per trade are applied, representing the average between the 25 to 31bp range normally paid for trading large-cap stocks on the US exchanges, as reported in Peterson and Sirri (2003) and Bessembinder (2003).

Figure 1 reports for each model-strategy pair the number of trades averaged across stocks.[18] It illustrates that, irrespective of the forecasting model employed, the two Directional strategies are the most trade intensive whereas the Top20 and Bottom20 strategies are the least trade-intensive. Thus one should expect that after transaction costs the profitability falls more dramatically in the former. The detailed statistics presented in Table 5 and summaries presented in Table 6 corroborate this.

[Figure 1 around here]

[Table 5 around here]

[Table 6 around here]

With reference to Table 6, the top two panels suggest that for the Directional strategy the number of stocks that outperform the B&H before transaction costs is 12 (SR) and 11 (alpha) whereas the bottom two panels suggest that this count falls sharply to 2 stocks (net SR) and 2 (net alpha). By contrast, in the case of the Top20 strategy the number of outperforming stocks afer

[18] The number of trades for each stock-model-strategy case is available from the authors upon request.

transaction costs at 10 (SR) and 7 (alpha) remains much closer to the pre-transaction costs counts at, respectively, 12 and 8. This is in line with the fact that the Top20 strategy involves a lower number of trades which lessens the impact of transaction costs. The ranking of forecasting models in terms of trading intensity varies from strategy to strategy. Thus, for instance, with the Top20 strategy where trading signals are triggered following large forecasted volatilities the largest trading intensity corresponds to GARCH-VOL and the smallest to GARCH. This is in line with the fact that, as shown in Fuertes, Izzeldin and Kalotychou (2009), GARCH-VOL forecasts are biased upwards, GARCH forecasts downwards and GARCH forecasts augmented with intraday prices lie somewhere in-between. Despite the differences across strategies, interestingly, a common feature is that the lowest trading intensity tends to be associated with GARCH forecasts.

Figure 2, Panel A (B) represents for the Top20 strategy the Sharpe ratio (alpha) associated with each of the six competing forecasting models for all stocks.

[Figure 2 around here]

The graph illustrates that the largest average Sharpe ratio and alpha measures net of transaction costs tend to correspond to the GARCH forecasts. GARCH-VOL forecasts appear as a close second best since they entail similar (or better) Sharpe ratios and alphas than the GARCH forecasts in 7 stocks: AXP, BA, CAT, GE, GM, JPM and KO.

As summarised in Table 6, several of the 70 stock-strategies still beat the corresponding passive B&H after transaction costs although, as expected, the count is reduced. According to the Sharpe ratio the number of stock-strategies that beat the B&H is 50 before transaction costs falling to 32 after transaction costs. According to the alpha the corresponding counts are, respectively, 40 (before) versus 23 (after). The cost-adjusted comparison of profitability measures across forecasting models is quite revealing. Invariably across criteria the GARCH model emerges most often as the most effective forecaster. Considering only the cases for which the passive B&H is beaten, on average across the five strategies the frequency with which the GARCH model is selected is

54% according to the Sharpe ratio (followed by GARCH-VOL with 15% frequency) and 30% according to alpha (followed closely by GARCH-VOL with 26%). It turns out also that the bottom-ranked model is either GARCH-RV or GARCH-RR with a frequency of wins at about 3-4%. Finally, we should note that GARCH-RBP tends to lie ahead of GARCH-RPV in the cost-adjusted profitability ranking. These results confirm the main finding from the previous sections, namely, that augmenting GARCH models with lagged intraday-return measures of volatility is not profitable for volatility-based trading strategies.

5 Conclusions

How to forecast daily volatility is a challenging question because, unlike prices and volume, volatility is not directly observable. A recent literature focuses on exploiting the intraday price variation and proposes several "realised" volatility estimators which are nonparametric by nature and so they do not rely on modeling approaches and assumptions. Most of the work so far focuses on the statistical evaluation of volatility forecasts, while the very important question of their economic relevance has received scant attention. This paper focuses on the economic significance of volatility forecasts and the role of high frequency data when stock market volatility forecasts are used for trading. To this end, it compares the realised variance, realised range, realised power variation and realised bipower variation estimators on the basis of their ability to produce good trading signals that materialize in trading profits. Our benchmark forecasts are obtained from the simple GARCH framework of Engle (1982) which casts the future variance as a polynomial of past squared returns. For completeness, a volume measure of intraday trading activity is also included in the horse race. The profitability of various long/short trading rules that exploit volatility signals is used to gauge the performance of the different volatility forecasts.

The findings suggest that from a trading viewpoint the use of intraday prices is not rewarded. The intraday variance estimators that have in earlier work been shown to enhance volatility forecasts in a statistically significant manner are dominated by the baseline GARCH forecasts. Interestingly, if any intraday information is worthwhile it comes in the form of volume rather than price fluctuations. Overall across stocks and trading strategies the baseline GARCH forecasts emerge as the top performer followed closely by the forecasts from GARCH augmented with lagged volume. This indicates that when the interest is in volatility-based trading, the predictive information in daily returns could be sufficient. Moreover, our analysis suggests that it is possible to devise volatility-based trading strategies for individual stocks that are profitable relative to the passive buy-and-hold even after transaction costs. The top performing strategy is the long only with a top 20% volatility threshold, namely, buying the stock only when its volatility exceeds the historical upper 20th percentile. This indirectly corroborates that the volatility-return relationship is stronger for extremely high levels of volatility, thereby rendering trading signals in that regime much more successful.

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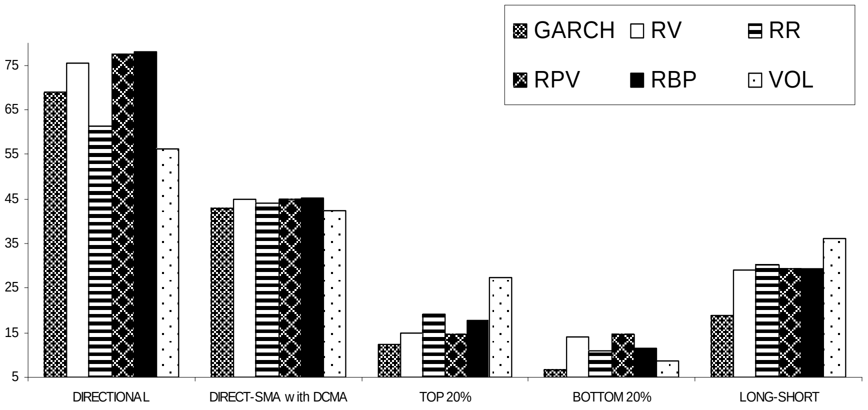
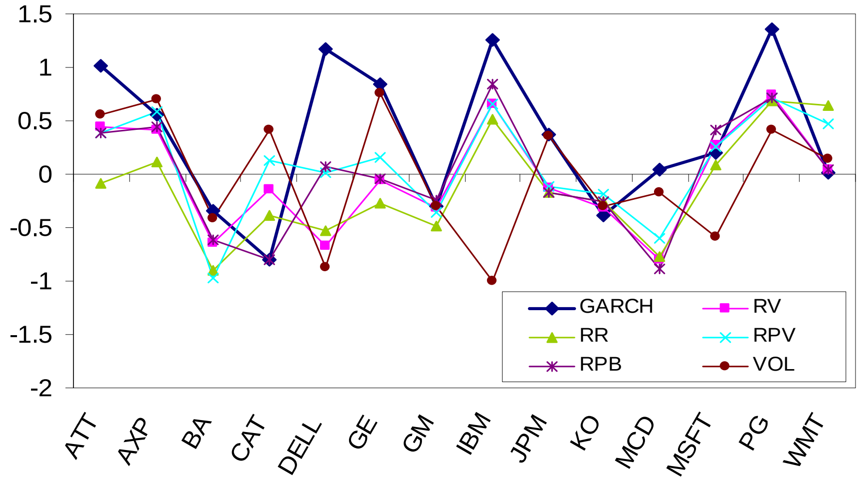


Figure 1. Average number of trading signals

A) Sharpe ratio net of transaction costs



B) Alpha net of transaction costs

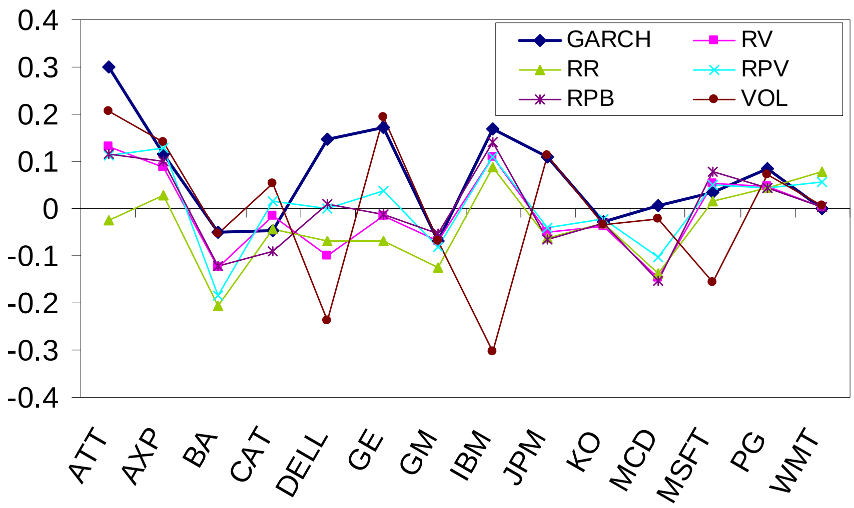


Figure 2. Risk-adjusted performance measures (Top20 strategy)

Table 1. Summary Statistics of Unconditional Daily Volatility Estimators and Daily Volume

	ATT	**AXP**	**BA**	**CAT**	**DELL**	**GE**	**GM**	**IBM**	**JPM**	**KO**	**MCD**	**MSFT**	**PG**	**WMT**
								Squared returns(r_t^2)						
Mean	5.150	4.683	3.940	3.991	8.965	3.481	3.567	3.714	5.535	2.740	3.189	4.765	2.690	4.021
StDev	10.141	9.289	8.108	7.279	20.529	7.206	6.251	7.890	19.972	6.093	7.610	8.328	6.597	8.522
StDev/Mean	1.969	1.983	2.057	1.823	2.289	2.070	1.752	2.124	3.608	2.223	2.386	1.747	2.452	2.119
Skewness	5.434	5.820	5.568	4.352	9.916	7.059	4.100	8.178	20.758	8.601	9.084	5.035	8.003	6.898
Kurtosis	46.480	56.130	47.390	29.840	160.129	82.450	27.220	113.350	586.580	124.030	121.660	44.530	92.770	87.457
								Realised variance(**RV**)						
Mean	4.506	4.673	4.078	3.782	8.170	3.648	3.021	3.572	5.622	2.836	3.550	4.441	2.905	4.140
StDev	4.356	5.065	3.950	3.176	7.689	3.776	2.950	3.663	7.717	2.417	3.337	3.892	3.080	4.298
StDev/Mean	0.966	1.083	0.968	0.839	0.941	1.035	0.976	1.025	1.372	0.852	0.940	0.876	1.470	1.038
Skewness	4.190	4.673	6.773	3.054	3.570	4.629	4.145	6.442	8.931	3.206	4.511	3.486	5.152	6.340
Kurtosis	31.610	32.030	105.240	17.800	25.870	38.220	33.070	92.930	136.670	19.070	35.830	24.560	49.260	90.930
								Realised range(**RR**)						
Mean	3.014	2.859	2.748	2.131	10.028	2.741	1.745	2.525	3.839	1.889	2.554	5.243	1.871	2.648
StDev	2.656	2.711	2.284	2.014	9.300	2.345	1.624	2.119	4.408	1.363	2.124	4.285	1.697	2.137
StDev/Mean	0.881	0.948	0.831	0.945	0.927	0.855	0.930	0.383	1.148	0.721	0.831	0.817	0.907	0.807
Skewness	3.671	3.239	3.509	11.102	3.830	3.765	3.357	3.557	7.050	2.624	3.662	3.144	4.556	2.872
Kurtosis	26.610	20.020	28.630	259.890	33.470	31.970	20.650	30.240	90.890	14.690	25.890	20.260	43.510	18.090
								Realised power variation(**RPV**)						
Mean	8.680	8.863	8.111	7.468	13.888	7.573	6.356	7.408	10.112	6.315	7.315	8.887	6.280	8.121
StDev	5.679	6.351	5.064	4.471	9.158	5.145	4.172	4.770	8.256	3.741	4.486	5.408	4.293	5.491
StDev/Mean	0.654	0.716	0.624	0.598	0.659	0.679	0.656	0.643	0.816	0.592	0.613	0.608	0.683	0.676
Skewness	2.832	2.659	3.130	2.161	2.396	2.978	2.469	2.367	4.875	2.293	2.895	2.252	2.856	2.832
Kurtosis	17.017	14.370	24.786	10.819	13.350	17.554	12.818	13.373	47.943	11.694	17.751	12.366	17.600	20.182
								Realised bipower variation(**RBP**)						
Mean	4.090	4.292	3.702	3.401	7.652	3.416	2.734	3.340	5.175	2.598	3.252	4.146	2.676	3.724
StDev	4.252	4.732	3.775	3.048	7.480	3.710	2.783	3.210	7.024	2.369	3.263	3.753	2.879	3.888
StDev/Mean	1.039	1.102	1.019	0.896	0.977	1.086	1.0179	0.961	1.357	0.911	1.003	0.905	1.075	1.044
Skewness	4.506	3.931	7.403	3.529	3.656	4.945	3.818	6.442	7.799	3.549	4.798	3.658	5.253	4.961
Kurtosis	34.320	25.60	124.150	23.790	25.350	42.870	25.730	92.930	101.450	22.800	40.060	28.230	51.290	51.810
								Trading volume ($VOL \times 10^{-7}$)						
Mean	0.247	0.438	0.317	0.155	3.950	1.480	0.293	0.714	0.695	0.368	0.419	6.394	0.266	0.608
StDev	2.233	0.215	0.179	0.084	3.086	0.667	0.184	0.343	0.350	0.170	0.246	2.743	0.176	0.252
StDev/Mean	9.040	0.491	0.565	0.542	0.781	0.451	0.628	0.480	0.504	0.462	0.587	0.429	0.662	0.414
Skewness	7.775	2.309	3.815	3.570	2.182	2.006	2.191	2.722	2.398	1.842	3.027	2.032	9.788	1.752
Kurtosis	128.364	14.241	29.778	34.609	9.507	10.277	10.172	18.462	15.756	8.883	19.028	11.460	189.924	8.817

The daily RV, RR, RPV and RBP are based on prices sampled at the 5-min frequency. RPV is computed for z=1.5.

Table 2. Frequency of Wins for each Forecasting Model using Statistical Criteria

Forecasting Model	Statistical Criteria							
	MSE	MAE	HMSE	AMAPE	MME(U)	MME(O)	GMLE	MZ-R2
Stock: American Express (AXP)								
GARCH	16.406	2.082	1.939	0.257	49.342	7.715	2.211	29.044
GARCH-RV	10.670**	1.794***	1.079**	0.226	28.719	7.065	2.143***	54.892
GARCH-RR	12.374***	2.225***	2.034***	0.279*	41.794	9.624***	2.198***	53.283
GARCH-RPV	10.321	1.666	0.828	0.211	29.614	5.615	2.129	56.967
GARCH-RBP	10.409	1.759**	1.087**	0.224**	28.988	6.876	2.141**	56.108
GARCH-VOL	18.239***	2.305**	38.958***	0.271***	49.766*	10.330*	2.255**	22.240**
Stock: IBM								
GARCH	4.096***	1.422	1.148	0.260	13.257	4.371	1.815	42.741
GARCH-RV	2.520**	1.101**	0.833***	0.220	6.477	3.114***	1.772**	63.962**
GARCH-RR	2.806***	1.272***	1.135***	0.248***	7.502**	3.703***	1.798***	64.974
GARCH-RPV	2.399	1.054	0.662	0.207	6.412	2.768	1.758	65.971
GARCH-RBP	2.605**	1.104***	0.817*	0.219	6.668	3.094***	1.772**	62.713*
GARCH-VOL	27.075***	4.718***	31.274***	0.517***	19.834**	30.737***	2.284***	3.468***

Frequency of Wins

Forecasting Model	MSE	MAE	HMSE	AMAPE	MME(U)	MME(O)	GMLE	MZ-R2	*Total*	%
GARCH	0	0	0	0	0	0	0	0	0	0%
GARCH-RV	2	3	2	3	4	1	1	1	17	15%
GARCH-RR	4	2	2	2	1	2	3	3	19	17%
GARCH-RPV	**7**	**8**	**10**	**8**	**5**	**11**	**8**	**7**	**64**	**57%**
GARCH-RBP	1	1	0	1	4	0	2	3	12	11%
GARCH-VOL	0	0	0	0	0	0	0	0	0	0%
Total	14	14	14	14	14	14	14	14	112	100%

The top two panels of the table report the estimated expected loss associated to each forecasting model using different loss functions. MSE is mean squared error, MAE is mean absolute error, HMSE is heteroskedasticity-adjusted MSE, AMAPE is adjusted mean absolute percentage error, MME(U) is mean mixed error with higher penalty for underpredictions, MME(0) is mean mixed error with higher penalty for overpredictions, GMLE is Gaussian maximum likelihood error, MZ- R^2 is the R^2 of the MIncer-Zarnowitz regression where the dependent variable is the realized volatility and the independent variable is the forecasted volatility. Bold indicates the top performer. *, **, *** denote that the forecasts of the model are significantly worse than those of the top performer (Diebold-Mariano test) at the 10%, 5% or 1% level. The bottom panel reports the number of stocks for which a forecasting model wins the race according to each criterion.

Table 3. Volatility-Based Trading Strategies: Summary Statistics

Stock	Model	Volatility-Based Trading Strategies																			
		Directional				Directional SMA-DCMA				Top20				Bottom20				Long-short			
		ΔEPV	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*
ATT	GARCH	6.08	-32.90	9.08	62	**71.95**	-1.99	**59.21**	34	**157.11**	40.15	**127.51**	22	80.75	1.31	64.56	0	**157.11**	40.15	127.51	22
	GARCH-RV	0.20	-39.92	-2.30	73	63.37	-6.61	51.72	39	124.02	26.48	105.36	35	75.06	-1.52	59.98	2	115.93	22.96	99.65	37
	GARCH-RR	**7.91**	-29.95	**13.86**	57	66.38	-4.71	54.80	39	89.31	11.08	80.40	42	79.82	0.84	63.80	1	88.29	10.57	79.58	43
	GARCH-RPV	-0.97	-41.71	-5.21	71	60.03	-8.46	48.72	43	116.84	23.22	100.07	32	79.51	0.80	63.73	8	115.16	22.59	99.06	40
	GARCH-RBP	7.67	-30.60	12.81	73	63.84	-6.34	52.17	40	122.47	25.71	104.11	38	75.42	-1.33	60.28	2	114.96	22.44	98.81	40
	GARCH-VOL	-0.88	-41.95	-5.61	55	21.25	-20.60	29.04	30	143.62	38.57	124.94	44	**85.95**	3.93	**68.81**	2	151.99	42.14	**130.74**	46
AXP	GARCH	-36.10	-1.33	-17.97	57	-44.78	-8.72	-24.12	48	-1.77	14.49	-4.82	5	-30.26	-1.38	-18.02	5	-8.89	11.46	-7.34	10
	GARCH-RV	-14.04	10.82	-7.87	54	-38.48	-5.20	-21.19	49	1.87	16.33	-3.29	19	-33.86	-3.16	-19.50	6	-10.99	10.70	-7.97	25
	GARCH-RR	-26.35	5.44	-12.35	31	-39.56	-5.68	-21.60	48	-9.14	11.75	-7.10	25	-27.40	0.07	-16.81	6	-13.56	9.89	-8.64	31
	GARCH-RPV	-40.71	-3.70	-19.95	58	-45.59	-9.09	-24.43	52	7.30	18.94	-1.11	14	-39.91	-6.34	-22.14	9	-13.96	9.48	-8.98	23
	GARCH-RBP	-24.61	5.49	-12.30	55	-48.91	-11.02	-26.04	50	0.58	15.95	-3.60	14	-32.99	-2.71	-19.12	2	-11.09	10.86	-7.83	16
	GARCH-VOL	-31.74	1.08	-15.97	58	-46.92	-9.91	-25.12	50	**10.09**	19.61	-0.56	12	-23.90	1.81	-15.37	10	**10.80**	20.20	-0.06	22
BA	GARCH	0.57	4.54	-3.02	86	-0.02	2.89	-4.56	46	-5.12	0.56	-6.72	16	-4.41	-0.08	-7.31	3	-8.01	-0.82	-8.00	19
	GARCH-RV	**26.24**	16.97	**8.51**	89	**8.74**	7.22	-0.54	46	-17.34	-5.22	-12.08	23	-8.58	-2.26	-9.34	7	-23.40	-8.56	-15.18	30
	GARCH-RR	-27.25	-9.29	-15.86	69	-4.01	1.06	-6.25	43	-32.93	-13.53	-19.79	26	-4.62	-0.28	-7.50	2	-35.15	-14.89	-21.05	28
	GARCH-RPV	3.13	6.16	-1.52	78	4.04	4.98	-2.61	40	-28.36	-11.51	-17.92	24	-8.54	-2.20	-9.28	8	-33.61	-14.58	-20.76	32
	GARCH-RBP	3.21	6.40	-1.30	88	-2.17	1.89	-5.49	44	-14.90	-3.73	-10.70	28	-6.65	-1.28	-8.43	5	-19.44	-6.19	-12.98	33
	GARCH-VOL	24.20	16.27	7.85	54	6.40	6.09	-1.59	35	**7.71**	6.66	-1.06	38	**0.60**	2.31	-5.09	1	**9.90**	7.71	-0.08	39
CAT	GARCH	-34.56	14.53	-13.60	53	-59.97	-0.16	-24.69	47	-52.78	2.38	-22.77	21	-61.15	-1.97	-26.06	2	-59.45	-0.93	-25.27	23
	GARCH-RV	-45.16	9.56	-17.35	62	-68.28	-4.60	-28.04	52	-50.58	3.87	-21.65	14	-72.43	-7.84	-30.49	11	-69.11	-5.52	-28.74	25
	GARCH-RR	-13.08	24.73	-5.89	51	-56.07	1.89	-23.15	48	-53.55	2.49	-22.69	20	-59.93	-1.37	-25.60	5	-58.94	-0.22	-24.73	25
	GARCH-RPV	-39.63	12.40	-15.21	58	-67.75	-4.29	-27.81	53	-45.04	6.63	-19.56	13	-68.57	-5.71	-28.88	8	-60.31	-0.75	-25.14	21
	GARCH-RBP	-9.27	26.33	-4.69	50	-61.40	-0.87	-25.23	47	-44.62	6.82	-19.42	52	-52.85	2.30	-22.83	11	-42.70	7.87	-18.63	63
	GARCH-VOL	**21.05**	38.59	**4.57**	48	-49.41	5.20	-20.64	45	-15.05	20.31	-9.24	43	-53.35	1.93	-23.12	1	-13.33	21.04	-8.68	44
DELL	GARCH	13.10	18.12	2.56	60	-8.15	3.66	-10.00	36	**23.81**	18.20	**2.63**	6	-16.24	-0.89	-13.95	12	**16.47**	15.64	**0.41**	18
	GARCH-RV	-7.31	9.16	-5.22	15	-19.44	-1.98	-14.90	38	-27.10	-6.09	-18.47	11	-23.84	-5.04	-17.56	14	-38.10	-11.97	-23.58	25
	GARCH-RR	-32.13	-5.46	-17.93	54	-17.64	-1.08	-14.12	39	-22.91	-4.07	-16.72	6	-27.24	-6.48	-18.81	30	-37.45	-11.44	-23.12	36
	GARCH-RPV	**23.43**	24.32	**7.95**	22	-14.39	0.62	-12.65	38	-7.89	4.35	-9.41	10	-29.44	-7.87	-20.02	19	-27.11	-5.10	-17.62	29
	GARCH-RBP	-1.52	12.36	-2.45	28	-15.23	0.19	-13.02	40	-5.57	4.93	-8.90	9	-18.85	-2.42	-15.29	8	-14.09	1.07	-12.26	17
	GARCH-VOL	-5.75	10.31	-4.23	53	-14.31	0.55	-12.70	39	-47.10	-15.65	-26.78	31	-30.74	-8.58	-20.63	23	-60.01	-23.89	-33.93	54

Table 3. Volatility-Based Trading Strategies: Summary Statistics (*cont.*)

Stock	**Model**	**Volatility-Based Trading Strategies**																			
		Directional				Directional SMA-DCMA				Top20				Bottom20				Long-short			
		ΔEPV	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*
GE	GARCH	29.45	5.73	13.68	79	29.12	3.04	10.79	37	67.07	22.28	31.47	10	19.51	-2.25	5.10	2	56.95	17.99	26.85	12
	GARCH-RV	32.68	7.47	15.54	90	29.97	3.46	11.23	38	25.89	3.88	11.69	14	25.35	0.84	8.42	9	24.49	3.40	11.17	23
	GARCH-RR	8.11	-4.36	2.84	70	14.17	-4.39	2.80	45	17.33	-0.22	7.28	20	23.11	-0.45	7.03	5	14.02	-1.95	5.42	25
	GARCH-RPV	29.19	5.67	13.61	90	25.33	1.16	8.77	35	36.70	9.37	17.58	14	23.71	0.04	7.56	5	33.34	7.99	16.11	19
	GARCH-RBP	**40.04**	10.90	**19.23**	91	29.42	3.18	10.94	36	25.55	3.66	11.45	12	**25.71**	0.99	**8.58**	9	24.50	3.34	11.10	21
	GARCH-VOL	30.17	6.78	14.80	57	**30.52**	3.84	**11.64**	39	**80.55**	29.44	**39.16**	24	17.27	-3.40	3.86	2	**66.07**	23.42	**32.69**	26
GM	GARCH	**20.73**	17.62	8.05	70	32.71	19.68	9.95	49	-18.11	-3.51	-11.37	8	-12.09	-2.84	-10.75	4	-25.25	-7.46	-15.00	12
	GARCH-RV	20.47	17.83	**8.25**	74	42.24	23.65	13.60	50	-17.59	-3.45	-11.31	8	-8.07	-0.77	-8.84	4	-21.29	-5.43	-13.13	12
	GARCH-RR	-6.65	5.11	-3.45	35	**52.17**	28.03	**17.62**	41	-24.17	-6.31	-13.94	20	-9.62	-1.59	-9.60	1	-28.85	-9.00	-16.40	21
	GARCH-RPV	15.21	15.41	6.03	68	38.97	22.27	12.33	49	-17.96	-3.58	-11.43	12	-15.00	-4.32	-12.11	7	-27.62	-8.94	-16.35	19
	GARCH-RBP	11.92	13.85	4.59	72	43.06	23.98	13.90	49	-14.77	-1.89	-9.87	8	-9.66	-1.59	-9.60	3	-20.01	-4.69	-12.45	11
	GARCH-VOL	-15.98	-1.18	-9.22	68	14.95	11.60	2.52	47	-13.84	-1.22	-9.26	16	-34.12	-14.77	-21.71	9	-41.19	-16.90	-23.67	25
IBM	GARCH	-21.73	-24.49	-17.25	38	39.29	7.81	18.13	34	**72.12**	22.39	**34.11**	12	21.17	-1.94	7.45	3	**62.36**	18.47	**29.81**	15
	GARCH-RV	1.73	-8.56	0.20	52	37.92	7.15	17.41	40	53.71	14.98	25.99	8	19.79	-2.62	6.71	10	43.45	10.53	21.11	18
	GARCH-RR	-8.90	-15.07	-6.93	43	32.43	4.54	14.55	39	51.68	14.14	25.06	12	20.66	-2.21	7.16	3	42.65	10.18	20.73	15
	GARCH-RPV	-2.57	-11.32	-2.82	49	41.84	9.01	19.45	40	53.71	14.98	25.99	8	13.15	-6.06	2.95	14	35.14	6.63	16.84	22
	GARCH-RBP	**6.92**	-5.39	**3.67**	58	**47.51**	11.71	**22.41**	39	62.63	19.02	30.41	10	24.34	-0.34	9.21	4	57.74	17.08	28.29	14
	GARCH-VOL	-13.68	-18.18	-10.33	21	41.90	9.18	19.63	35	-14.59	-18.95	-11.18	48	**28.62**	1.64	**11.38**	7	-14.23	-18.68	-10.89	55
JPM	GARCH	-2.04	0.75	-8.53	67	16.97	7.25	-2.62	42	37.41	19.46	8.46	21	2.28	-1.85	-10.89	5	28.92	15.73	5.08	26
	GARCH-RV	14.48	9.39	-0.69	104	31.58	13.89	3.40	47	-6.98	-0.47	-9.64	11	-18.57	-13.02	-21.04	12	-30.21	-14.55	-22.43	23
	GARCH-RR	17.15	12.24	1.91	63	**36.82**	16.58	**5.85**	41	-7.06	-0.08	-9.28	18	-5.35	-5.77	-14.45	7	-19.11	-7.06	-15.62	25
	GARCH-RPV	20.33	12.36	2.01	108	30.91	13.50	3.05	48	-4.40	0.96	-8.34	13	-11.15	-8.61	-17.03	14	-21.86	-8.93	-17.32	27
	GARCH-RBP	**28.99**	16.66	**5.92**	111	26.70	11.54	1.27	49	-10.09	-2.44	-11.42	10	-15.04	-10.92	-19.13	14	-29.62	-14.21	-22.12	24
	GARCH-VOL	15.34	10.51	0.33	59	22.26	9.84	-0.28	41	**46.92**	24.83	**13.34**	36	**2.79**	-1.69	-10.75	6	**38.52**	21.14	**9.99**	42
KO	GARCH	13.89	12.62	4.21	87	-1.52	4.02	-3.76	43	-7.80	0.87	-6.67	9	-18.97	-4.91	-12.03	10	-20.26	-5.33	-12.41	19
	GARCH-RV	**30.99**	20.28	**11.29**	102	-2.40	3.61	-4.13	48	-9.40	0.44	-7.07	10	-16.57	-3.60	-10.81	25	-19.35	-4.43	-11.58	35
	GARCH-RR	15.16	13.77	5.27	66	-17.27	-3.72	-10.92	49	-3.85	3.27	-4.46	18	-11.56	-1.08	-8.48	18	-9.22	0.83	-6.71	36
	GARCH-RPV	13.45	12.51	4.10	101	-10.65	-0.47	-7.92	48	-6.00	2.17	-5.47	11	-14.55	-2.51	-9.80	24	-14.25	-1.68	-9.03	35
	GARCH-RBP	21.77	16.42	7.71	107	-7.82	1.00	-6.55	49	-8.58	0.92	-6.62	10	-24.61	-8.02	-14.90	19	-26.47	-8.36	-15.22	29
	GARCH-VOL	10.60	11.26	2.94	74	-8.82	0.43	-7.08	46	-9.09	0.59	-6.93	10	-24.71	-8.05	-14.93	20	-26.99	-8.70	-15.53	30

Table 3. Volatility-Based Trading Strategies: Summary Statistics (*cont.*)

Stock	Model	Volatility-Based Trading Strategies																			
		Directional				Directional SMA-DCMA				Top20				Bottom20				Long-short			
		ΔEPV	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*	*ΔEPV*	*R*	*ΔR*	*N(T)*
MCD	GARCH	54.17	23.79	21.04	92	8.69	0.38	-1.85	51	**27.82**	9.64	**7.21**	26	9.91	0.29	-1.94	9	25.05	8.54	6.13	35
	GARCH-RV	27.05	10.94	8.48	82	8.15	-0.03	-2.25	46	-2.33	-4.70	-6.81	34	7.40	-0.84	-3.04	26	-6.54	-6.72	-8.79	60
	GARCH-RR	65.26	29.15	26.28	84	6.25	-0.78	-2.99	50	1.14	-2.81	-4.97	38	3.38	-2.95	-5.10	16	-6.82	-6.90	-8.96	54
	GARCH-RPV	42.95	18.47	15.85	104	10.71	1.21	-1.03	50	5.49	-0.66	-2.86	32	-5.35	-7.47	-9.53	21	-11.01	-9.27	-11.28	53
	GARCH-RBP	9.82	2.56	0.29	102	6.22	-1.03	-3.23	51	-4.20	-5.83	-7.93	33	10.83	0.84	-1.40	18	-5.45	-6.27	-8.35	51
	GARCH-VOL	**86.75**	36.86	**33.82**	90	**22.43**	7.09	**4.72**	47	24.21	7.88	5.49	30	**18.07**	4.49	**2.17**	21	**30.64**	11.27	**8.80**	51
MSFT	GARCH	-3.70	-10.23	-5.04	63	-0.95	-11.18	-6.04	43	36.00	8.71	14.99	13	17.02	-2.19	3.46	3	28.19	4.95	11.01	16
	GARCH-RV	-6.92	-11.89	-6.80	62	-3.29	-12.55	-7.49	44	41.63	11.94	18.41	17	28.50	3.73	9.72	12	46.88	14.61	21.23	29
	GARCH-RR	-3.67	-10.12	-4.92	71	1.54	-9.80	-4.58	43	35.32	8.64	14.91	19	16.65	-2.16	3.50	12	27.14	4.92	10.98	31
	GARCH-RPV	-11.49	-14.75	-9.82	59	-3.75	-12.81	-7.77	43	41.43	11.82	18.28	17	25.74	2.44	8.36	15	43.45	13.06	19.59	32
	GARCH-RBP	**7.47**	-3.37	**2.22**	62	-2.20	-11.91	-6.82	45	**47.38**	14.41	**21.02**	16	22.57	0.78	6.60	10	45.61	13.82	20.39	26
	GARCH-VOL	-9.82	-13.27	-8.25	44	-6.78	-14.51	-9.57	46	11.76	-1.48	4.22	50	20.30	-0.54	5.21	1	8.50	-3.27	2.32	51
PG	GARCH	-3.36	11.51	-2.17	71	-31.50	-3.05	-14.95	44	-4.51	10.09	-3.41	1	-28.82	-1.57	-13.65	23	-11.02	7.42	-5.76	24
	GARCH-RV	-11.83	7.28	-5.88	104	-30.48	-2.57	-14.52	46	-12.07	6.56	-6.51	2	-20.32	3.01	-9.63	37	-9.70	8.35	-4.94	39
	GARCH-RR	-5.50	10.44	-3.11	83	-33.29	-4.04	-15.81	45	-12.12	6.54	-6.53	3	-34.11	-4.17	-15.93	38	-24.89	0.80	-11.56	41
	GARCH-RPV	-16.24	5.22	-7.69	117	-30.31	-2.48	-14.45	47	-11.78	6.71	-6.38	3	-22.54	1.87	-10.63	37	-11.86	7.29	-5.87	40
	GARCH-RBP	-7.68	9.44	-3.98	99	-31.66	-3.16	-15.05	47	-11.78	6.71	-6.38	3	-26.03	0.10	-12.19	37	-16.79	4.90	-7.97	40
	GARCH-VOL	-1.90	12.88	-0.96	17	-37.68	-6.28	-17.78	49	-9.48	9.29	-4.12	1	-31.71	-3.31	-15.17	1	-19.90	4.31	-8.49	2
WMT	GARCH	-5.23	-4.61	-4.21	82	-17.06	-12.76	-12.40	45	11.71	2.24	2.67	3	**25.00**	9.14	**9.60**	11	26.79	10.14	10.60	14
	GARCH-RV	-22.91	-14.78	-14.42	92	-17.41	-12.98	-12.62	45	12.20	2.93	3.36	4	15.90	4.91	5.35	21	18.06	6.59	7.04	25
	GARCH-RR	-22.26	-14.34	-13.98	81	-16.79	-12.60	-12.23	48	**26.98**	10.18	**10.65**	3	6.67	0.16	0.58	8	22.93	8.94	9.40	11
	GARCH-RPV	-31.96	-20.73	-20.40	102	-16.09	-12.22	-11.85	43	22.18	7.88	8.34	3	16.20	5.15	5.59	14	**28.93**	11.97	**12.44**	17
	GARCH-RBP	-25.79	-16.62	-16.27	96	-16.68	-12.55	-12.18	45	12.20	2.93	3.36	4	17.67	5.79	6.24	20	19.87	7.48	7.93	24
	GARCH-VOL	-19.68	-13.32	-12.96	89	-10.28	-8.94	-8.56	44	12.56	2.64	3.07	2	10.42	2.34	2.77	16	12.83	3.69	4.12	18
Average across stocks																					
	GARCH	2.23	2.55	-0.94	69	2.48	0.78	-0.49	43	24.50	12.00	12.38	12	0.26	-0.80	-1.74	7	19.21	9.71	10.26	19
	GARCH-RV	3.26	3.18	-0.59	75	3.01	0.89	-0.59	45	8.28	4.82	4.85	15	-2.16	-2.01	-2.86	14	1.44	1.43	1.71	29
	GARCH-RR	-2.30	0.88	-2.45	61	1.80	0.38	-1.14	44	4.00	2.93	2.34	19	-2.11	-1.96	-2.87	11	-2.78	-0.38	-0.77	30
	GARCH-RPV	0.29	1.45	-2.36	78	1.66	0.21	-1.30	45	11.59	6.52	6.27	15	-4.05	-2.91	-3.66	15	2.46	2.13	2.26	29
	GARCH-RBP	4.93	4.60	1.10	78	2.19	0.47	-0.92	45	11.16	6.23	6.11	18	-0.73	-1.27	-2.28	12	5.50	3.51	3.48	29
	GARCH-VOL	6.33	4.04	-0.23	56	-1.04	-0.46	-2.56	42	16.30	8.75	8.65	28	-1.04	-1.56	-2.33	9	10.97	5.96	6.24	36

The table reports the excess $ End-of-Period Value (ΔEPV) of the strategy over that of the B&H strategy, the annualised % return (R) and volatility (σ) of the strategy. N(T) denotes the number of in/out roundtrip trades. Bold indicates the best model/strategy in terms of return among those that beat the B&H.

Table 4. Risk-Adjusted Performance of Volatility-Based Trading Strategies

Stock	**Model**	**Volatility-Based Trading Strategies**									
		Directional		Directional SMA-DCMA		Top20		Bottom20		Long-Short	
		ΔSR	*Δ α*	*ΔSR*	*Δ α*	*ΔSR*	*Δ α*	*ΔSR*	*Δ α*	*ΔSR*	*Δ α*
ATT	GARCH	0.03	5.54	**0.41**	**36.09**	**1.92**	**77.59**	0.62	—	**1.92**	77.59
	GARCH-RV	-0.07	-1.41	0.12	31.53	1.47	64.19	-0.28	36.57	1.35	60.71
	GARCH-RR	**0.10**	**8.41**	0.28	33.41	0.93	48.97	-0.26	38.90	0.91	48.46
	GARCH-RPV	-0.11	-3.18	0.00	29.70	1.37	60.97	0.51	38.86	1.34	60.37
	GARCH-RBP	0.08	7.77	0.14	31.80	1.45	63.42	-0.22	36.75	1.34	60.19
	GARCH-VOL	-0.13	-3.41	0.17	17.69	1.60	76.07	**1.35**	**41.94**	1.69	**79.60**
AXP	GARCH	-0.63	-21.21	-1.37	-28.43	0.10	-5.60	-0.90	-21.19	-0.07	-8.59
	GARCH-RV	-0.20	-9.29	-1.05	-24.97	0.16	-3.80	-1.07	-22.95	-0.12	-9.35
	GARCH-RR	-0.40	-14.61	-1.05	-25.45	-0.09	-8.32	-0.70	-19.76	-0.18	-10.16
	GARCH-RPV	-0.71	-23.58	-1.34	-28.81	0.26	-1.23	-1.39	-26.09	-0.19	-10.56
	GARCH-RBP	-0.38	-14.53	-1.53	-30.71	0.12	-4.17	-1.01	-22.50	-0.13	-9.20
	GARCH-VOL	-0.54	-18.84	-1.46	-29.61	**0.38**	-0.54	-0.45	-18.05	**0.36**	**0.04**
BA	GARCH	-0.04	-3.18	-0.07	-4.79	-0.24	-7.11	-0.48	-7.71	-0.33	-8.46
	GARCH-RV	**0.53**	**9.09**	**0.24**	-0.51	-0.53	-12.81	-1.21	-9.87	-0.70	-16.11
	GARCH-RR	-0.59	-16.85	-0.21	-6.59	-0.84	-21.00	-0.99	-7.91	-0.89	-22.34
	GARCH-RPV	0.02	-1.58	0.07	-2.71	-0.86	-19.03	-0.94	-9.81	-1.00	-22.05
	GARCH-RBP	0.03	-1.36	-0.15	-5.77	-0.44	-11.35	-1.01	-8.90	-0.56	-13.78
	GARCH-VOL	0.47	8.39	0.16	-1.63	0.21	-1.07	**0.53**	-5.35	**0.29**	-0.02
CAT	GARCH	-0.43	-17.74	-1.04	-32.20	-0.76	-29.72	-2.15	-34.01	-1.29	-33.00
	GARCH-RV	-0.63	-22.66	-1.33	-36.58	-0.71	-28.28	-2.61	-39.81	-1.51	-37.54
	GARCH-RR	-0.09	-7.68	-0.91	-30.18	-0.84	-29.63	-2.41	-33.41	-1.08	-32.30
	GARCH-RPV	-0.53	-19.85	-1.31	-36.29	-0.48	-25.56	-2.07	-37.70	-1.11	-32.85
	GARCH-RBP	-0.02	-6.09	-1.08	-32.91	-0.46	-25.35	-0.75	-29.79	-0.41	-24.31
	GARCH-VOL	**0.46**	**6.00**	-0.71	-26.92	0.58	-12.04	-0.23	-30.16	**0.64**	-11.31
DELL	GARCH	0.18	2.91	-0.19	-11.26	**0.96**	**3.10**	-0.56	-15.72	**0.50**	**0.57**
	GARCH-RV	-0.13	-5.94	-0.57	-16.83	-0.85	-20.83	-1.06	-19.81	-1.11	-26.64
	GARCH-RR	-0.57	-20.35	-0.52	-15.95	-0.76	-18.83	-0.96	-21.23	-1.05	-26.11
	GARCH-RPV	**0.30**	**8.99**	-0.40	-14.27	-0.19	-10.54	-1.16	-22.61	-0.66	-19.87
	GARCH-RBP	-0.04	-2.78	-0.43	-14.69	-0.10	-9.95	-0.78	-17.23	-0.37	-13.77
	GARCH-VOL	-0.10	-4.77	-0.41	-14.34	-0.98	-30.32	-1.22	-23.31	-1.21	-38.45
GE	GARCH	0.40	12.67	0.39	10.06	1.23	28.93	-0.50	4.84	1.00	24.70
	GARCH-RV	0.47	14.35	0.43	10.46	0.33	10.78	0.15	7.89	0.30	10.31
	GARCH-RR	0.03	2.65	-0.22	2.71	0.16	6.72	-0.23	6.61	0.10	5.01
	GARCH-RPV	0.40	12.57	0.21	8.19	0.55	16.17	0.05	7.09	0.48	14.82
	GARCH-RBP	**0.62**	**17.74**	0.40	10.20	0.32	10.56	**0.17**	**8.04**	0.30	10.24
	GARCH-VOL	0.42	13.69	**0.44**	**10.85**	**1.31**	**35.99**	-0.69	3.70	**1.06**	**30.06**
GM	GARCH	**0.34**	8.67	0.90	10.75	-0.43	-12.19	-1.34	-11.48	-0.59	-16.09
	GARCH-RV	0.33	**8.87**	1.18	14.67	-0.44	-12.13	-0.76	-9.44	-0.52	-14.08
	GARCH-RR	-0.10	-3.71	**1.33**	**18.99**	-0.52	-14.95	-1.22	-10.25	-0.62	-17.60
	GARCH-RPV	0.25	6.48	1.09	13.31	-0.44	-12.26	-1.41	-12.94	-0.67	-17.55
	GARCH-RBP	0.20	4.93	1.21	14.99	-0.36	-10.59	-1.02	-10.24	-0.49	-13.36
	GARCH-VOL	-0.31	-9.87	0.43	2.77	-0.33	-9.94	-2.11	-23.26	-0.96	-25.41

Table 4. Risk-Adjusted Performance of Volatility-Based Trading Strategies (*cont.*)

Stock	Model	**Volatility-Based Trading Strategies**									
		Directional		Directional SMA-DCMA		Top20		Bottom20		Long-Short	
		ΔSR	*Δ α*	*ΔSR*	*Δ α*	*ΔSR*	*Δ α*	*ΔSR*	*Δ α*	*ΔSR*	*Δ α*
IBM	GARCH	-0.62	-15.44	0.76	16.49	**1.86**	**30.84**	-0.21	6.88	**1.44**	**26.97**
	GARCH-RV	-0.03	0.22	0.71	15.84	1.10	23.50	-0.27	6.21	0.79	19.10
	GARCH-RR	-0.24	-6.20	0.52	13.26	1.03	22.65	-0.25	6.62	0.77	18.75
	GARCH-RPV	-0.13	-2.49	0.85	17.67	1.10	23.50	-0.61	2.82	0.57	15.25
	GARCH-RBP	**0.07**	**3.34**	**1.02**	**20.34**	1.31	27.47	0.02	8.46	1.15	25.56
	GARCH-VOL	-0.33	-9.26	0.82	17.83	-0.37	-10.01	**0.44**	**10.42**	-0.36	-9.75
JPM	GARCH	-0.19	-9.19	0.13	-2.70	0.43	9.23	-0.67	-11.66	0.30	5.56
	GARCH-RV	0.08	-0.75	0.51	3.84	-0.22	-10.41	-1.66	-22.69	-0.59	-24.29
	GARCH-RR	0.13	2.07	**0.60**	**6.49**	-0.21	-10.05	-1.08	-15.53	-0.39	-16.93
	GARCH-RPV	0.17	2.20	0.51	3.46	-0.18	-8.99	-1.04	-18.34	-0.44	-18.74
	GARCH-RBP	**0.31**	**6.41**	0.40	1.52	-0.28	-12.35	-1.35	-20.62	-0.59	-23.95
	GARCH-VOL	0.10	0.41	0.26	-0.16	**0.55**	**14.53**	-0.85	-11.51	**0.43**	**10.89**
KO	GARCH	0.37	4.51	**0.05**	-3.97	-0.34	-7.08	-1.09	-12.78	-0.89	-13.19
	GARCH-RV	**0.80**	**12.07**	-0.01	-4.36	-0.35	-7.51	-0.87	-11.48	-0.68	-12.31
	GARCH-RR	0.34	5.61	-0.74	-11.62	-0.12	-4.71	-0.61	-9.00	-0.31	-7.12
	GARCH-RPV	0.35	4.39	-0.48	-8.41	-0.21	-5.80	-0.72	-10.40	-0.48	-9.60
	GARCH-RBP	0.54	8.24	-0.31	-6.95	-0.31	-7.02	-1.62	-15.84	-0.97	-16.19
	GARCH-VOL	0.26	3.18	-0.38	-7.51	-0.34	-7.36	-1.57	-15.88	-1.01	-16.53
MCD	GARCH	0.92	21.32	-0.10	-1.75	**0.62**	**7.34**	-0.20	-1.83	0.48	6.25
	GARCH-RV	0.42	8.64	-0.13	-2.15	-0.36	-6.82	-0.29	-2.95	-0.43	-8.81
	GARCH-RR	1.05	26.60	-0.18	-2.90	-0.25	-4.93	-0.58	-5.03	-0.44	-8.96
	GARCH-RPV	0.74	16.07	-0.03	-0.93	-0.14	-2.82	-0.94	-9.49	-0.56	-11.30
	GARCH-RBP	0.03	0.38	-0.22	-3.14	-0.43	-7.93	-0.09	-1.29	-0.42	-8.35
	GARCH-VOL	**1.53**	**34.23**	**0.42**	**4.88**	0.50	5.60	**0.36**	**2.31**	**0.64**	**8.94**
MSFT	GARCH	-0.23	-4.66	-0.75	-5.52	0.62	14.10	-1.03	3.38	0.39	10.39
	GARCH-RV	-0.27	-6.31	-0.85	-6.87	0.72	17.27	**0.56**	**9.23**	**0.82**	**19.91**
	GARCH-RR	-0.22	-4.54	-0.67	-4.15	0.58	14.03	-0.28	3.42	0.37	10.37
	GARCH-RPV	-0.37	-9.12	-0.87	-7.13	0.71	17.13	0.34	7.96	0.74	18.36
	GARCH-RBP	**0.03**	**2.11**	-0.81	-6.24	**0.87**	**19.73**	0.10	6.32	0.81	19.15
	GARCH-VOL	-0.29	-7.66	-0.93	-8.81	0.08	4.03	-0.75	5.02	0.02	2.26
PG	GARCH	**0.03**	-2.41	-1.31	-16.76	**0.72**	-3.78	-1.04	-15.30	-0.10	-6.41
	GARCH-RV	-0.21	-6.60	-1.31	-16.29	0.15	-7.27	-0.54	-10.78	-0.14	-5.51
	GARCH-RR	-0.02	-3.49	-1.55	-17.73	0.14	-7.30	-1.23	-17.87	-0.73	-12.96
	GARCH-RPV	-0.39	-8.63	-1.31	-16.20	0.16	-7.14	-0.64	-11.91	-0.21	-6.56
	GARCH-RBP	-0.10	-4.46	-1.38	-16.87	0.16	-7.14	-0.81	-13.66	-0.40	-8.92
	GARCH-VOL	-0.05	-1.08	-1.68	-19.94	-0.24	-4.62	-1.76	-17.02	-0.53	-9.54
WMT	GARCH	-0.22	-4.10	-1.25	-12.09	0.23	2.70	**0.76**	**9.53**	**0.77**	10.50
	GARCH-RV	-0.69	-14.16	-1.29	-12.30	0.21	3.36	0.36	5.36	0.38	6.98
	GARCH-RR	-0.66	-13.72	-1.23	-11.92	**0.78**	**10.50**	-0.04	0.67	0.53	9.28
	GARCH-RPV	-1.01	-20.02	-1.23	-11.55	0.61	8.25	0.36	5.59	0.67	**12.28**
	GARCH-RBP	-0.78	-15.97	-1.24	-11.88	0.21	3.36	0.42	6.23	0.44	7.87
	GARCH-VOL	-0.73	-12.68	-0.95	-8.32	0.31	3.10	0.14	2.81	0.23	4.13

The table reports the incremental annualised Sharpe Ratio (ΔSR) and annualised % alpha (Δα) of the strategy relative to the benchmark B&H strategy. Bold indicates the best model/strategy among those that beat the B&H. — indicates that the strategy generates no trading signals and amounts to holding the risk-free rate.

Table 5. Performance of Volatility-Based Trading Strategies Net of Transaction Costs

Stock	Model	Volatility-Based Trading Strategies									
		Directional		Directional SMA-DCMA		Top20		Bottom20		Long-short	
		ΔNSR	*ΔN α*	*ΔNSR*	*ΔN α*	*ΔNSR*	*ΔN α*	*ΔNSR*	*ΔN α*	*ΔNSR*	*ΔN α*
ATT	GARCH	-0.15	-5.02	-0.14	**27.32**	**1.64**	**69.36**	0.63	N/A	**1.64**	**69.36**
	GARCH-RV	-0.26	-12.38	-0.47	22.00	1.07	52.53	-0.38	36.11	0.94	48.77
	GARCH-RR	-0.07	-1.95	-0.27	23.68	0.54	36.80	-0.54	38.70	0.52	36.08
	GARCH-RPV	-0.29	-13.68	-0.63	19.45	1.01	50.56	0.04	36.72	0.90	47.54
	GARCH-RBP	-0.14	-5.07	-0.46	22.01	1.02	50.89	-0.33	36.29	0.90	47.38
	GARCH-VOL	-0.27	-11.57	0.04	11.41	1.18	60.20	**1.22**	**41.45**	1.25	62.97
AXP	GARCH	-1.19	-35.75	-2.24	-39.91	0.03	-6.83	-1.10	-22.39	-0.21	-11.49
	GARCH-RV	-0.74	-24.83	-1.96	-37.12	-0.11	-9.62	-1.26	-24.39	-0.43	-16.33
	GARCH-RR	-0.68	-23.41	-1.89	-37.31	-0.40	-15.66	-0.94	-21.25	-0.54	-18.79
	GARCH-RPV	-1.25	-37.99	-2.23	-41.12	0.06	-5.60	-1.63	-28.24	-0.46	-16.89
	GARCH-RBP	-0.91	-29.57	-2.37	-42.33	-0.07	-8.44	-1.07	-22.88	-0.32	-13.56
	GARCH-VOL	-1.11	-33.98	-2.34	-41.38	**0.18**	-4.30	-0.87	-20.68	**0.08**	-5.66
BA	GARCH	-1.11	-25.50	-1.00	-17.26	-0.54	-11.34	-0.64	-8.40	-0.65	-13.43
	GARCH-RV	-0.68	-16.65	-0.72	-13.51	-0.83	-18.55	-1.62	-11.61	-1.07	-23.29
	GARCH-RR	-1.19	-32.76	-0.98	-18.09	-1.10	-26.89	-1.22	-8.32	-1.17	-28.58
	GARCH-RPV	-0.92	-22.37	-0.73	-13.89	-1.16	-24.60	-1.36	-11.81	-1.36	-29.19
	GARCH-RBP	-0.99	-24.54	-1.00	-17.62	-0.80	-18.42	-1.36	-10.12	-0.96	-21.87
	GARCH-VOL	-0.27	-7.95	-0.58	-11.60	-0.61	-11.62	0.40	-5.49	-0.55	-10.95
CAT	GARCH	-1.06	-33.53	-1.78	-44.27	-1.75	-35.36	-2.27	-34.37	-2.22	-38.96
	GARCH-RV	-1.31	-40.09	-2.11	-49.26	-1.08	-32.07	-3.10	-42.40	-2.03	-43.71
	GARCH-RR	-0.71	-24.29	-1.68	-42.74	-1.32	-35.00	-2.79	-34.59	-1.64	-38.83
	GARCH-RPV	-1.17	-36.68	-2.10	-49.24	-0.81	-29.17	-2.39	-39.59	-1.53	-38.30
	GARCH-RBP	-0.64	-22.61	-1.81	-44.88	-1.74	-39.56	-1.37	-32.69	-1.76	-40.59
	GARCH-VOL	-0.21	-11.47	-1.46	-39.12	-0.53	-25.42	-0.46	-30.26	-0.50	-25.07
DELL	GARCH	-0.41	-15.34	-0.87	-21.11	**0.82**	**1.30**	-0.86	-18.82	**0.16**	-4.92
	GARCH-RV	-0.26	-10.53	-1.20	-26.76	-1.02	-23.51	-1.45	-23.28	-1.44	-32.40
	GARCH-RR	-1.01	-33.60	-1.18	-26.21	-0.88	-20.26	-1.54	-28.57	-1.50	-34.40
	GARCH-RPV	**0.09**	**1.45**	-1.06	-24.46	-0.35	-13.24	-1.57	-27.20	-1.01	-27.07
	GARCH-RBP	-0.29	-11.32	-1.11	-25.21	-0.28	-12.39	-1.01	-19.22	-0.65	-18.28
	GARCH-VOL	-0.54	-19.98	-1.11	-24.65	-1.23	-37.14	-1.71	-28.82	-1.50	-47.16
GE	GARCH	-0.46	-8.06	-0.53	0.10	**1.07**	25.71	-0.60	4.42	**0.82**	20.96
	GARCH-RV	-0.51	-9.54	-0.53	0.21	0.16	6.94	-0.21	5.52	0.05	4.03
	GARCH-RR	-0.55	-14.36	-1.04	-8.42	-0.04	1.45	-0.59	5.37	-0.15	-1.45
	GARCH-RPV	-0.57	-10.91	-0.63	-1.07	0.38	12.13	-0.14	**5.84**	0.27	9.39
	GARCH-RBP	-0.42	-6.91	-0.50	**0.48**	0.18	7.28	-0.22	5.67	0.07	4.51
	GARCH-VOL	-0.17	-2.09	-0.46	0.29	0.99	**27.76**	-0.78	3.29	0.73	**21.58**
GM	GARCH	-0.35	-12.25	-0.02	-4.64	-0.48	-14.16	-1.49	-12.41	-0.68	-18.98
	GARCH-RV	-0.38	-13.15	0.18	-1.53	-0.49	-14.11	-0.97	-10.38	-0.62	-17.04
	GARCH-RR	-0.37	-13.58	**0.52**	**5.02**	-0.67	-19.87	-1.22	-10.37	-0.77	-22.62
	GARCH-RPV	-0.39	-13.52	0.12	-2.42	-0.54	-15.28	-1.67	-14.64	-0.83	-22.09
	GARCH-RBP	-0.46	-15.83	0.21	-0.95	-0.42	-12.60	-1.17	-10.91	-0.57	-16.08
	GARCH-VOL	-0.89	-26.98	-0.41	-11.04	-0.47	-14.09	-2.28	-25.22	-1.12	-30.20

Table 5. Performance of Volatility-Based Trading Strategies Net of Transaction Costs (*cont.*)

Stock	Model	Volatility-Based Trading Strategies									
		Directional		Directional SMA-DCMA		Top20		Bottom20		Long-short	
		ΔNSR	*ΔN α*	*ΔNSR*	*ΔN α*	*ΔNSR*	*ΔN α*	*ΔNSR*	*ΔN α*	*ΔNSR*	*ΔN α*
IBM	GARCH	-0.89	-23.08	0.04	6.61	**1.56**	**26.95**	-0.32	6.19	**1.11**	**22.26**
	GARCH-RV	-0.45	-12.18	-0.11	4.41	0.95	21.09	-0.63	3.66	0.50	13.83
	GARCH-RR	-0.55	-15.86	-0.24	2.37	0.82	19.03	-0.36	5.93	0.53	14.37
	GARCH-RPV	-0.51	-13.88	0.00	6.04	0.95	21.09	-1.03	-0.65	0.24	9.05
	GARCH-RBP	-0.39	-10.85	**0.19**	**8.69**	1.13	24.34	-0.16	7.48	0.91	21.22
	GARCH-VOL	-0.49	-13.99	0.12	7.55	-0.70	-20.02	-0.36	**8.72**	-0.69	-19.79
JPM	GARCH	-0.73	-26.16	-0.47	-14.38	**0.20**	2.60	-0.86	-12.87	**0.03**	-2.36
	GARCH-RV	-0.79	-27.91	-0.25	-9.83	-0.30	-13.26	-1.93	-25.40	-0.73	-29.43
	GARCH-RR	-0.38	-15.93	-0.05	-6.07	-0.34	-14.78	-1.29	-17.20	-0.55	-23.02
	GARCH-RPV	-0.75	-26.75	-0.29	-10.58	-0.28	-12.43	-1.34	-21.68	-0.61	-25.18
	GARCH-RBP	-0.67	-24.24	-0.39	-12.41	-0.35	-14.87	-1.68	-23.87	-0.73	-29.35
	GARCH-VOL	-0.40	-16.15	-0.34	-11.85	0.18	**2.80**	-1.17	-12.99	0.02	-2.15
KO	GARCH	-1.04	-19.78	-1.32	-15.55	-0.66	-9.43	-1.43	-15.24	-1.33	-17.92
	GARCH-RV	-0.91	-17.47	-1.47	-17.17	-0.59	-10.12	-1.63	-17.81	-1.30	-21.03
	GARCH-RR	-0.61	-13.31	-1.77	-23.75	-0.54	-9.61	-1.28	-13.69	-1.01	-16.59
	GARCH-RPV	-1.20	-23.00	-1.78	-20.70	-0.46	-8.73	-1.45	-16.56	-1.11	-18.58
	GARCH-RBP	-1.10	-21.55	-1.62	-19.68	-0.54	-9.64	-2.28	-20.43	-1.48	-23.15
	GARCH-VOL	-0.89	-17.62	-1.69	-19.43	-0.57	-9.97	-2.24	-20.71	-1.54	-23.70
MCD	GARCH	-0.28	-6.73	-1.08	-15.14	**0.02**	-0.17	-0.62	-4.17	-0.23	-3.68
	GARCH-RV	-0.65	-14.08	-1.09	-14.27	-0.83	-15.28	-1.15	-9.73	-1.15	-22.90
	GARCH-RR	-0.01	-0.43	-1.08	-15.89	-0.79	-14.55	-1.15	-9.12	-1.10	-21.70
	GARCH-RPV	-0.61	-13.77	-1.13	-14.18	-0.63	-11.14	-1.50	-14.61	-1.19	-23.61
	GARCH-RBP	-1.12	-25.02	-1.27	-16.34	-0.90	-16.05	-0.79	-6.08	-1.08	-20.50
	GARCH-VOL	**0.18**	**3.80**	-0.61	-8.37	-0.20	-2.90	-0.38	-3.48	-0.36	-5.63
MSFT	GARCH	-0.77	-19.16	-1.43	-15.63	0.39	10.36	-1.30	2.70	0.13	5.95
	GARCH-RV	-0.77	-20.34	-1.54	-17.04	0.46	12.23	**0.03**	**5.95**	0.39	11.16
	GARCH-RR	-0.81	-20.72	-1.38	-14.42	0.28	8.57	-0.70	0.34	-0.07	1.83
	GARCH-RPV	-0.82	-22.10	-1.53	-17.05	0.45	12.09	-0.23	3.90	0.28	8.86
	GARCH-RBP	-0.52	-13.29	-1.51	-16.70	**0.61**	**14.88**	-0.33	3.69	**0.41**	**11.34**
	GARCH-VOL	-0.62	-17.74	-1.58	-19.16	-0.39	-8.64	-0.88	4.87	-0.46	-10.41
PG	GARCH	-1.40	-22.49	-2.83	-27.78	0.67	-3.92	-1.79	-21.25	-0.77	-13.19
	GARCH-RV	-2.41	-33.60	-2.87	-27.84	0.06	-7.71	-1.47	-20.97	-1.04	-16.77
	GARCH-RR	-1.71	-26.33	-2.86	-28.88	0.00	-8.03	-2.19	-27.57	-1.68	-24.18
	GARCH-RPV	-2.65	-37.89	-2.79	-28.00	0.03	-7.86	-1.56	-21.72	-1.12	-17.70
	GARCH-RBP	-2.03	-30.86	-2.82	-28.59	0.03	-7.86	-1.71	-23.30	-1.31	-20.08
	GARCH-VOL	-0.35	-6.43	-2.62	-31.74	-0.27	-5.07	-1.81	-17.13	-0.56	-10.10
WMT	GARCH	-1.16	-23.42	-2.08	-22.23	0.08	1.99	**0.44**	**6.08**	**0.41**	6.14
	GARCH-RV	-1.58	-33.44	-2.11	-22.42	0.11	2.36	-0.13	-0.46	-0.05	-0.04
	GARCH-RR	-1.46	-31.05	-2.11	-22.72	**0.71**	**9.73**	-0.24	-1.40	0.33	6.13
	GARCH-RPV	-1.96	-39.63	-2.04	-21.32	0.54	7.49	0.03	1.42	0.36	**6.95**
	GARCH-RBP	-1.70	-35.55	-2.07	-22.04	0.11	2.36	-0.04	0.64	0.02	1.06
	GARCH-VOL	-1.75	-31.55	-1.86	-18.68	0.21	2.67	-0.21	-1.78	-0.14	-1.07

The table reports the incremental annualised cost-adjusted Sharpe Ratio (ΔNSR) and annualised % cost-adjusted alpha (ΔNa) of the strategy relative to the benchmark B&H strategy. Bold indicates the best model/strategy among those that beat the B&H.

Table 6. Frequency of Wins for each Forecasting Model Using Profitability Criteria

Forecasting Model	Volatility-Based Trading Strategies: Directional	Directional SMA-DCMA	Top20	Bottom20	Long-short	*Total*	%
A. Sharpe ratio							
GARCH	2	**2**	**4**	1	**4**	13	26%
GARCH-RV	2	1	0	1	1	5	10%
GARCH-RR	1	2	**1**	0	0	4	8%
GARCH-RPV	1	0	0	0	0	1	2%
GARCH-RBP	**4**	1	1	1	0	7	14%
GARCH-VOL	2	**2**	**6**	**4**	**6**	**20**	**40%**
Total	12	8	12	7	11	*50*	100%
B. Alpha							
GARCH	0	1	**4**	1	2	8	20%
GARCH-RV	3	0	0	1	1	5	13%
GARCH-RR	1	**2**	1	0	0	4	10%
GARCH-RPV	1	0	0	0	1	2	5%
GARCH-RBP	**4**	1	1	1	0	7	18%
GARCH-VOL	2	**2**	2	**3**	**5**	**14**	**35%**
Total	11	6	8	6	9	*40*	100%
C. Sharpe Ratio net of transaction costs							
GARCH	0	0	**7**	1	**6**	14	**54%**
GARCH-RV	0	**1**	0	1	0	2	8%
GARCH-RR	0	0	1	0	0	1	4%
GARCH-RPV	**1**	0	0	0	1	2	8%
GARCH-RBP	0	**1**	1	0	1	3	12%
GARCH-VOL	**1**	0	1	**2**	0	4	15%
Total	2	2	10	4	8	*26*	100%
D. Alpha net of transaction costs							
GARCH	0	1	**3**	1	**2**	**7**	**30%**
GARCH-RV	0	0	0	1	0	1	4%
GARCH-RR	0	1	1	0	0	2	9%
GARCH-RPV	**1**	0	0	1	1	3	13%
GARCH-RBP	0	**2**	1	0	1	4	17%
GARCH-VOL	**1**	0	2	**2**	1	6	26%
Total	2	4	7	5	5	*23*	100%

The table refers only to the stock-strategies (out of 70 cases available) for which the corresponding B&H of the individual stock is outperformed (shaded entry) according to each criteria. The figures reported are the number of stocks for which a given model wins the race. For instance, Panel A reports 12 cases (or stocks) outperforming the B&H with the Top20 strategy according to the Sharpe ratio, 6 of which pertain to GARCH-VOL signals; in the last column, 40% indicates that the race is won by GARCH-VOL signals in 20 out of a total of 50 stock-strategy cases that outperform the B&H. Bold denotes the forecasting model that wins the race more often.