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# Daily Volume, Intraday and Overnight Returns for Volatility Prediction: Profitability or Accuracy?

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**Abstract**

This article presents a comprehensive analysis of the relative ability of three information sets —daily trading volume, intraday returns and overnight returns — to predict equity volatility. We investigate the extent to which statistical accuracy of one-day-ahead forecasts translates into economic gains for technical traders. Various profitability criteria and utility-based switching fees indicate that the largest gains stem from combining historical daily returns with volume information. Using common statistical loss functions, the largest degree of predictive power is found instead in intraday returns. Our analysis thus reinforces the view that statistical significance does not have a direct mapping onto economic value. As a byproduct, we show that buying the stock when the forecasted volatility is extremely high appears largely profitable, suggesting a strong return-risk relationship in turbulent conditions.

**JEL Classification**: C53; C32; C14.

**Keywords**: Conditional variance forecasting; Trading rules; Realized volatility; Directional change prediction.

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# 1 Introduction

Nonparametric estimators of asset price variability based on intraday data known as "realized volatilities" have the appealing feature of yielding precise measures of *ex post* daily volatility without requiring any modeling assumptions. It has been shown that realized volatilities can improve the statistical accuracy of daily forecasts from historical volatility models (Blair et al., 2001; Fuertes et al., 2009). There is also evidence based on statistical criteria that the overnight information flow triggered by interactions across stock exchanges in different time zones, cross-listed stocks and news released outside regular trading hours has predictive content for the subsequent daytime volatility (Gallo, 2001; Tsiakas, 2008). On the other hand, the evidence on the ability of trading volume to improve the statistical accuracy of volatility forecasts is rather weak (Brooks, 1998; Donaldson and Kamstra, 2005).

Many volatility forecast competitions are available in the literature but most of them rely solely on statistical loss functions as evaluation method. A new branch of forecasting studies has emerged that utilizes economic loss functions motivated not only but their practical relevance but also by the notion that, as first noted by Satchell and Timmermann (1995), superior forecast accuracy does not necessarily imply trading profitability. For instance, Fleming et al. (2003) show that dynamic mean-variance asset allocation based on realized and overnight covariance forecasts brings performance gains. Brownlees and Gallo (2010) and Fuertes and Olmo (2012) support the use of realized volatilities to obtain more adequate economic capital measures. However, relatively less is known about whether there is any incentive for investors to complement historical daily return models with additional information such as intraday price variation, overnight price variation or daily trading volume.

A well-known fact is that it is easier to predict the second moment than the first moment of the daily return distribution because volatility is a highly persistent process. Practitioners commonly deploy simple market timing strategies that exploit volatility forecasts as trading signals; see e.g., Northington (2009), Larsen (2004), Rattray and Balasubramanian (2003) and Lasky (2001). In contrast, serial dependence in returns remains a controversial empirical issue strongly refuted by financial economics theory (Fama, 1970). Christoffersen and Diebold (2006) show a direct connection between asset return volatility and the direction of price changes which has important implications for investors pursuing market timing strategies. Volatility predictability can lead to return sign predictability vindicating technical trading rules that seek to anticipate changes in the direction of market moves.

This paper seeks to contribute to a novel but still sparse literature which utilizes economic measures such as profitability criteria to rank volatility forecasting models. It is, to the best of our knowledge, the first study that investigates the relative information content in *intraday* price variation, *overnight* price variation and daily *volume* for volatility-based technical trading.[1] Our framework focuses on simple intuitive technical trading rules which offer a feasible "laboratory" for ranking volatility forecasts. A common aspect across the trading rules deployed is that they build upon the positive nexus between stock returns and volatility dictated by asset pricing theory. Using panel data models, we begin by confirming empirically a significantly positive contemporanous relation between daily stock returns and realized variance which appears stronger at extreme volatility levels. Baseline volatility forecasts are obtained from a standard GARCH model based on individual (and portfolio) equity

[1] The expression 'volatility-based technical trading' is used here to denote trading strategies that are based on buy/sell signals implied from volatility forecasts. This differs from what is called 'volatility trading' in the literature, namely, trading strategies that treat volatility, i.e. the VIX index and, more recently, VIX futures, as an asset class (see Hafner and Wallmeier, 2007, and Konstantinidi et al., 2008 ). It also differs from 'volatility timing' which refers to the use of (co)variance forecasts in dynamic optimal portfolio construction (see Fleming et al, 2003).

prices sampled at daily frequency. Then we augment the daily GARCH model with realized volatility, overnight return or trading volume information. We investigate the relative effectiveness of these three information sets in generating incremental profitability defined as positive risk- and cost-adjusted returns over and above those extracted from the standard GARCH forecasts. To accommodate non-Gaussianity in the technical trading returns, we gauge relative profitability through the Sortino ratio, Leland's alpha and a quadratic utility-matching performance fee for various degrees of relative risk aversion. Transaction costs are also factored in. Among the battery of purely statistical criteria considered for forecast evaluation, we include the de facto Mean Square Error and $R^2$ of Mincer-Zarnowitz regressions.

Our empirical analysis based on a 1761-day observation window for 14 large S&P500 stocks and the S&P500 index produces various key findings. The statistical criteria indicate that augmenting the GARCH model with realized volatilities (constructed from squared intraday returns) leads to the largest forecast accuracy gains. Volatility-based technical trading simulations confirm, first, that exploiting additional information over and above daily returns affords incremental profitability. For instance, conditioning the standard daily return-based GARCH forecasts additionally on daily volumes, squared overnight returns or realized volatilities leads to attractive gains in net annualized Sortino ratios from 0.003 to 6.28 points, Leland's alphas from 0.02% to 22.07% and net annualized switching fees from 0.02% to 22.63%. Second, trading volume is shown to be the most effective volatility predictor from the viewpoint of economic value, followed by overnight returns, while realized volatility is the least effective. Kendall's *tau* rank correlations based on the notion of concordance and discordance confirm a low association between profitability criteria and statistical criteria, indicating that de facto forecast accuracy measures such as the Mean Square Error and Mean Absolute Error may be of little use to traders. As a byproduct, we show that simple technical trading rules perform reasonably well vis-à-vis the Buy-and-Hold; the leading rule buys the stock at day $t + 1$ open if the predicted volatility exceeds the top 20th percentile of historical realized volatilities.

The rest of the paper unfolds as follows. Section 2 provides some relevant background literature. Section 3 presents the data, volatility forecasting models and statistical evaluation measures. Section 4 outlines the technical trading rules. Section 5 discusses the empirical findings before concluding in a final section.

## 2 Background Literature

A burgeoning empirical literature seeking improvements in volatility forecasting has been naturally encouraged by two stylized properties of daily asset returns, namely, pervasive memory in volatility and very little autocorrelation in levels. A significant link between volatility and *trading volume*, possibly reflecting information about changes and disagreement in investors' expectations, has also been documented in many studies (Karpoff, 1987; Najand and Yung, 1991; Jacobs and Onochie, 1998; Rahman et al., 2002). In fact, several of those studies show that adding contemporaneous volume as regressor in GARCH models yields in-sample fit improvements. However, lagged volume has failed to produce gains in volatility forecast accuracy (Brooks, 1998; Donaldson and Kamstra, 2005; Fuertes et al., 2009).

The increasing availability of high-frequency (intraday) data in the last decade has permitted many empirical finance studies to employ *realized volatilities*. Thus, for various asset classes (including FX, equities, bonds and commodities) it has been shown that the use of intraday price information can improve the forecast accuracy of models based on daily prices; see, e.g. Taylor and Xu (1997), Koopman et al. (2005), Pong et al. (2004), Liu and Maheu (2009) and Fuertes and Olmo (2012).

On the other hand, the evidence thus far on the predictive content of *overnight returns* is less conclusive. Gallo (2001) shows for various large-cap stocks that augmenting GARCH models with overnight returns improves Mean Absolute Errors but the evidence from Mean Square Errors is more mixed. Using data on various global stock market indices to estimate stochastic volatility models and a Bayesian evaluation framework, Tsiakas (2008) establishes that there is substantial predictive ability in financial information accumulated during overnight hours.

Our paper relates to a recent branch of the literature that utilizes decision-based loss functions in order to judge forecasts through the lens of their economic value to the user rather than just relying on statistical significance; see, e.g. Fleming et al. (2003), Abhyankar et al. (2005), della Corte et al. (2010). Satchell and Timmermann (1995) were the first to discuss theoretically the 'disconnect' between statistical accuracy and profitability, illustrating it through a simple trading rule that holds the local currency if it is predicted to appreciate against the US$.

We employ a volatility-based technical trading framework as laboratory to assess the relative merit of intraday return, overnight return and volume information. Several studies provide the background motivation for this choice. Larsen (2004) demonstrates that the implied volatility index VIX can be used as oscillator to identify equity market turning points since historical data suggests that, when VIX reaches low levels, markets tend to be at the top and reversal follows, and when VIX reaches high levels markets are at a trough and ready to move upward. Christoffersen and Diebold (2006) argue in favour of volatility-based strategies built upon the link between volatility and market direction: the stylized volatility clustering renders volatility highly forecastable and induces return sign persistence which can be exploited for market timing. Northington (2009) proposes volatility indicators for enhancing technical trading rules and providing profitable exit signals. Harvey and Whaley (1992) test the profitability of implied volatility for trading S&P100 options and conclude that there are no net gains. By contrast, Noh et al. (1994) find that trading straddles on the S&P500 index using daily GARCH forecasts can reap significant profits after transaction costs. Konstantinidi et al. (2008) show that while statistical accuracy measures and the mean correct directional-change prediction suggest successful predictability of various implied volatility indices, trading strategies are unable to yield abnormal profits.

# 3 Data and Forecasting Methodology

The analysis is based on high-frequency transaction prices from *Tick Data* for individual stocks and an equity index spanning the period 02/01/97 to 31/12/03 ($T = 1761$ days). We focus on 14 large-cap S&P500 stocks which are chosen to ensure wide sector representation: American Express (AXP), AT&T (ATT), Boeing (BA), Caterpillar (CAT), DELL, General Electric (GE), General Motors (GM), IBM, J.P. Morgan (JPM), Coca-Cola (KO), McDonald (MCD), Microsoft (MSFT), Procter & Gamble (PG) and WAL-MART (WMT).[2] Among these, AXP and JPM are financials; BA, CAT, GE, GM are industrials; MSFT, DELL, IBM are technology; PG, WMT, KO, MCD pertain to the consumer goods sector, and AT&T is telecommunication. The volatility forecasting competition is also conducted using the S&P500 index as proxy for diversified portfolio trading.

## 3.1 Daily GARCH Models and Augmentation Variables

In order to measure realized volatility, the trading day [9:30am-4:00pm] is divided into $M$ intervals of 5-minute length. The 5-minute sampling interval has been

[2] Two stocks are listed on Nasdaq (DELL and MSFT) while the remaining are NYSE listed.

shown to be short enough for the daily volatility dynamics to be captured with reasonable accuracy, and long enough for the adverse effects of market microstructure frictions not to be excessive. The price at the start of the $j$th intraday interval is computed as the average of the closing and opening prices of intervals $j-1$ and $j$, respectively. Thus the $j$th intraday return on day $t$ is computed as $r_{t,j} = \left(\frac{\log(p^c_{t,j})+\log(p^o_{t,j+1})}{2} - \frac{\log(p^c_{t,j-1})+\log(p^o_{t,j})}{2}\right), j = 2, ..., M-1$, where $p^c_{t,j}$ ($p^o_{t,j}$) is the closing (opening) price of the $j$th intraday interval. The first-interval return is $r_{t,1} = \left(\frac{\log(p^c_{t,1})+\log(p^o_{t,2})}{2} - \log(p^o_{t,1})\right)$ and the last-interval return is $r_{t,M} = \left(\log(p^c_{t,M}) - \frac{\log(p^c_{t,M-1})+\log(p^o_{t,M})}{2}\right)$. Aggregation of the $M = 78$ intraday returns gives the daily return defined as the open-to-close log price difference, $r_t = \sum_{j=1}^{M} r_{t,j} = \log(\frac{p^c_{t,M}}{p^o_{t,1}}) = \log(\frac{p^c_t}{p^o_t})$. The inter-daily (close-to-close) return comprises the overnight return and the daily return, i.e. $\log(\frac{p^c_t}{p^c_{t-1}}) = \log(\frac{p^o_t}{p^c_{t-1}}) + \log(\frac{p^c_t}{p^o_t})$.

The GARCH$(r, s)$ model treats volatility as latent and can be formalized as[3]

$$r_t = \mu + \varepsilon_t,\ \varepsilon_t = z_t\sqrt{h_t},\ z_t \sim iid(0,1) \quad (1a)$$

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{s} \beta_j h_{t-j} + \eta v_{t-1} \quad (1b)$$

where $r_t$ are daily daily open-to-close returns as defined above, and $z_t$ are the demeaned standardized returns. The lag orders $(r, s)$ are chosen so as to remove serial dependence in squared daily returns. The parameters are estimated by Quasi Maximum Likelihood. The conditional variance equation (1b) has a straightforward financial interpretation. In the simplest GARCH$(1, 1)$ with $\eta = 0$, a trader predicts the asset return volatility as a weighted sum of a long term average variance (embed-

[3]We deploy the Ljung-Box statistic to test the null hypothesis of no residual autocorrelation. For 9 stocks the conditional mean equation in (1a) is appropriate. For the remaining 6 stocks (ATT, DELL, GM, IBM, PG and WMT) we employ instead an ARMA$(p, q)$ equation $r_t = \mu + \sum_{i=1}^{p} \theta_i r_{t-i} + \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}$ with appropriate orders $p$ and $q$ so as to whiten the residual sequence. The GARCH equation (2b) for CAT, JPM, KO and MCD has lags $r = 2$ and $s = 1$ whereas for all other stocks a GARCH(1,1) suffices to absorb the autocorrelation in squared daily returns.

ded in the constant $\omega$), the previous period volatility news ($\varepsilon_{t-1}^2$) and the previous variance forecast ($h_{t-1}$). As additional predictor ($v_{t-1}$) we consider either realized volatility, trading volume or squared overnight returns; henceforth, augmentation variables. Next, we discuss each of the three candidate augmentation variables in turn. Hereafter, equation (1b) with $\eta = 0$ is referred to as standard GARCH.

A large number of realized volatility measures have been developed in recent years since Andersen et al. (1998) originally proposed the realized variance, or aggregation of intraday squared returns, as *ex post* non-parametric measure of daily volatility. We opt for the *realized power variation* (RPV) measure introduced by Barndoff-Nielsen and Shephard (2004) which is defined as

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

where $M$ is the number of equal-length intraday intervals, $\delta = 1/M$, and $\mu_\lambda = E\,|\mu|^\lambda = 2^{\lambda/2} \frac{\Gamma(\frac{1}{2}(\lambda+1))}{\Gamma(\frac{1}{2})}$ with $\mu \sim N(0, 1)$. RPV becomes realized absolute variation for power order $\lambda = 1$, and realized variance for $\lambda = 2$. Our motivation for employing the RPV measure (with $\lambda = 1.5$) is both theoretical and empirical. Barndorff-Nielsen and Shephard (2004) show analytically and via simulations that RPV is robust to jumps which can be regarded as large outliers inducing biases in model estimates and forecasts. The empirical literature has shown that despite the predominant use of squared returns, absolute returns raised to the power $1 \leq \lambda \leq 1.5$ are extremely good forecasters of future volatility as they are more persistent; see, e.g. Ghysels et al. (2006), Forsberg and Ghysels (2007), and Liu and Maheu (2009).

Our other two candidates for the augmentation term $v_{t-1}$ in equation (1b) are daily *trading volume* ($VOL$), defined as the total number of shares traded on day $t-1$, and the squared *overnight return* ($OVN$) defined as $[\log(\frac{p_t^o}{p_{t-1}^c})]^2$.

The sample is divided into an estimation period of 1261 days ($T_0$) and a holdout period of 500 days ($T_1$) so that ($T = T_0 + T_1$).[4] The initial 1261-day length window is sequentially rolled and the model parameter estimation is repeated to obtain 500 out-of-sample 1-day-ahead volatility forecasts. This rolling estimation approach offers some 'shield' against structural breaks (shifts) in the volatility process.

## 3.2 Statistical Analysis

We begin by discussing the main distributional properties of daily returns, daily squared returns as an unbiased volatility proxy and the three candidates we are considering as predictors of future volatility — realized power variation, trading volume and squared overnight returns.[5] The sample autocorrelation function of daily and squared daily returns alongside the Ljung-Box Q test and ARCH LM test confirm that there is far more predictability in the second than in the first moment of the return process. Both daily volatility measures ($r_t^2$ and RPV) exhibit large positive skewness and kurtosis. By using mean volume as proxy for trading activity, stocks can be ranked from more to less liquid as technology, financials, consumer goods and industrials. Average trading volume of the index is several times that of individual stocks. Among all three predictors of future daily volatility — RPV, volume and squared overnight returns — volume generally exhibits the lowest dispersion relative to its mean (coefficient of variation) which, in turn, indicates that it is the least noisy while the squared overnight return lies at the other extreme. The unreported Ljung-Box Q test for squared overnight returns corroborates that the volatility clustering typical of daily returns is not a distinctive feature of overnight returns, in line with the evidence in Gallo (2001). This might be due to the overnight

[4] Thus the out-of-sample period comprises about 1/4 of the total sample as in Koopman et al. (2005), Liu and Maheu (2009), Ghysels et al. (2006) and Fuertes et al. (2009).

[5] For space constraints, we do not report the detailed statistics here but they are tabulated in Appendices A1 and A2 of the longer working paper version of this article (see Fuertes et al., 2013).

return noisiness that renders the autocorrelation signal difficult to pick up.

Let $\sigma_t^2$ denote the latent daytime volatility process that we are seeking to forecast. Following the recent literature, an appropriate target ($\tilde{\sigma}_t^2$) for forecast evaluation is the sum of open-to-close intraday squared returns. The accuracy of the $m$th model forecasts, $\{h_{t,m}\}_{t=1}^{T_1}$, is first gauged through a battery of statistical criteria based on the out-of-sample forecast errors $\{\tilde{\sigma}_t^2 - h_{t,m}\}_{t=1}^{T_1}$. More precisely, we employ mean error measures based either on *symmetric* loss functions such as the Mean Absolute Error (MAE), Mean Square Error (MSE), heteroskedasticity-adjusted MSE (HMSE), and adjusted mean absolute percentage error (AMAPE), or *asymmetric* loss functions such as the Mean Mixed Error (MME) that assigns different penalty to under(U)- and over(O)- predictions, the Gaussian Maximum Likelihood Error (GMLE) and the loss function implicit in the Mincer-Zarnowitz regressions.[6]

Table 1 reports the above statistical forecast accuracy criteria alongside the equal predictive ability test of Diebold and Mariano (1995; DM) and the forecast encompassing $t$-test of Harvey et al. (1998; ENC-T) for three stocks — financial (AXP), industrial (CAT) and technology (MSFT) — and the S&P500 index.[7]

[Table 1 around here]

A pervasive finding across statistical loss functions is that the GARCH-VOL and GARCH-OVN forecasts have inferior accuracy than those from the GARCH-RPV model that exploits intraday data. The superior forecast accuracy of the intraday-augmented GARCH models versus the volume- or overnight-augmented models is statistically significant as suggested by the DM test at the 5% significance level

[6] A description of these statistical metrics can be found in Fuertes et al. (2009). The $R^2$ of the Mincer-Zarnowitz levels regression ($MZ$-$R^2$ henceforth), $\tilde{\sigma}_t^2 = a + bh_{t,m} + e_t, t = 1, ..., 500$, measures the information content of the forecasts; $h_{t,m}$ is unbiased for $\tilde{\sigma}_t^2$ if $a = 0$ and $b = 1$.

[7] Results for the remaining 11 stocks are qualitatively similar and not reported to preserve space.

or better. The statistical significance of the forecast accuracy gains of augmented GARCH models (versus the standard GARCH) is gauged by means of the ENC-T test.[8] We find that realized volatility, unlike volume, adds significant information to the historical GARCH forecasts. Albeit with notably smaller ENC-T statistics, conditioning the GARCH forecasts on squared overnight returns also affords significant forecast accuracy improvements. The win counts across the 14 individual stocks and S&P500 portfolio are clearcut: unanimously across all 15 assets, the lowest mean forecast error and the largest $MZ$-$R^2$ correspond to the GARCH-RPV forecasts.

The last column of Table 1 summarizes the outcome of the non-parametric market timing $t$-test of Pesaran and Timmermann (1992; PT-T). This test is aimed at comparing the proportion of correctly predicted directional changes in volatility with the probability of correct predictions under the null of independence between directional forecasts and realizations. The PT-T statistics reported in Table 1 unambiguously indicate that all of the GARCH models considered (i.e., standard or augmented) can correctly predict the sign of the volatility change since the null hypothesis of no market timing ability is strongly refuted at the 1% level.

In the next section we present a trading framework to evaluate the competing volatility forecasts. Building on the theoretical positive risk-return nexus that represents one of the cornerstones of Merton's (1973) dynamic asset pricing theory, various trading strategies are designed to exploit the volatility forecasts. The return-risk tradeoff remains a matter of controversy in the empirical literature and is not the main focus of this paper. Nevertheless, in order to set the stage for the trading simulations, we explore the intertemporal risk-return relation in a high-frequency framework following Bali and Peng (2006). Accordingly, we run a pooled regression

[8] For nested models the DM test statistic is non-Gaussian, resulting in undersized tests with low power, so the results are interpreted with caution. The ENC-T test null is that model A encompasses model B and the alternative is that model B contains additional predictive information.

across stocks of daily returns, $r_t$, on daily realized variances, $\tilde{\sigma}_t^2$, over the estimation window ($T_0 = 1261$ days).[9] Next, the return-variance observations $\{(r_t, \tilde{\sigma}_t^2)\}_{t=1}^{1261}$ are arranged according to the ordered realized variance $\tilde{\sigma}_t^2$ to create five equal-sized subsamples using as boundaries the 80th, 60th, 40th and 20th percentile. Thus the top quintile $Q_1$ contains the extremely high volatility days above the 80th percentile, and the bottom quintile $Q_5$ contains the extremely low volatility days below the 20th percentile. We estimate a return-risk regression per quintile. Two panel estimation approaches are employed: pooled OLS (POLS) that assumes homogeneity across stocks and Random Effects (RE) that allows for stock return heterogeneity induced by unobserved random factors which are uncorrelated with the stock realized variance. The reported $t$-statistics are based on panel corrected standard error (PCSE) covariances that account for cross-section contemporaneous correlation as well as different error variances in each cross-section.[10] Table 2 sets out the results.

[Table 2 around here]

The correlation between returns and realized variances over the whole sampling distribution is significantly positive at 3.34%. However, the correlation is notably larger in the top and bottom volatility quintiles, at 8.59% and 5.82%, respectively, than in the intermediate quintiles. Both the POLS and RE estimators yield significantly positive slope coefficients in the top quintile $Q_1$ and in the bottom quintiles $Q_4$ and $Q_5$. Overall the evidence suggests that the daily return-risk relation is positive and stronger at the tails of the volatility distribution, particularly, the right tail.

[9] Bali and Peng (2006) are the first to use daily realized variances to examine the risk-return link for the aggregate stock market. In addition, they use risk measures obtained from GARCH models estimated with 5-minute returns and daily implied volatilities. All three risk measures suggest that the intertemporal risk-return relation is positive and statistically significant.

[10] For details on the PCSE methodology see Beck and Katz (1995). Wooldridge's panel test statistic for zero autocorrelation in the residuals of the quintile regressions is insignificant throughout.

# 4 Volatility-Based Technical Trading Strategies

The out-of-sample volatility forecasts obtained from standard and augmented GARCH models are translated into trading signals using the strategies that we outline next. On days when the strategy at hand suggests no position in the stock (or index) the investor earns the risk-free rate proxied by the 3-month US Treasury bill.

## 4.1 Directional-Change Strategies

Let $h^m_{t+1}$ denote the volatility forecast for day $t+1$ obtained from model $m$ using information up to day $t$. Motivated by the significant results from the market timing PT-T test reported in Table 1, we employ two long-only strategies which exploit the directional-change predictive ability of the models. In the first long-only strategy, called *Directional*, the stock (or index) is bought at the opening of day $t+1$ if the forecast for $t+1$ represents an increase in volatility with respect to the 'observed' or realized volatility on day $t$ (i.e., $h^m_{t+1} - \tilde{\sigma}^2_t > 0$).[11] The asset will be held for $s$ days, namely, until a sell or decrease-in-volatility signal is obtained for day $t+s+1$ (i.e., $h^m_{t+s+1} - \tilde{\sigma}^2_{t+s} < 0$) when the asset is sold at the opening.

A potential problem with the *Directional* strategy is very frequent trading and hence, large transaction costs. Short-term moving averages deployed as heuristic trading rules have been shown to enhance market timing strategies; see e.g., Lee et al. (2003) and Corrado and Lee (1992). We overlay a 5-day Simple Moving Average (SMA) and a 5-day/20-day Double Crossover Moving Average (DCMA) stop-loss rule to the Directional strategy in order to: i) reduce the number of trades (achieved by the SMA), and ii) limit the potential losses caused by large price falls (achieved

[11] For the GARCH model augmented with the squared overnight return, all trading strategies are deployed using the 10:00am price (instead of the opening 9:30am price) as the buy or sell price. This is because it is not feasible for an investor to trade on day $t+1$ at the open price if that price is precisely required for the GARCH-OVN model to generate the day $t+1$ volatility forecast.

by the DCMA).[12] Thus the *Directional-SMA-DCMA* strategy buys the asset at the opening of day $t+1$ if three conditions are met: 1) the day $t+1$ variance forecast is greater than the realized variance on day $t$, 2) the opening price on day $t+1$ is greater than the $SMA_{t+1}$ signal, and 3) no stop-loss signal arises from the $DCMA_{t+1}$.

## 4.2 Level-Driven Strategies

We want to consider volatility level-driven strategies for two reasons. A first motivation is provided by our empirical finding that the positive daily return-volatility link appears stronger at the tails of the volatility distribution. A second motivation comes from the stylized fact that at extremely high (low) volatility levels equity markets tend to bottom out (top up) and reversal occurs (Larsen, 2004).

We start by deploying a long-only trading strategy, called $Top20$, as follows. The daily realized variance sequence over the estimation window, $\{\tilde{\sigma}_t^2\}_{t=1}^{1261}$ is ordered to identify the 80th percentile (top quintile) volatility $\kappa_{80,t}$. In line with the notion of time-varying risk, we roll the window forward to generate a sequence of high-volatility thresholds, $\{\kappa_{80,t}\}_{t=1}^{500}$, one per out-of-sample day. If the volatility forecasted for day $t+1$ is high ($h_{t+1}^m > \kappa_{80,t}$), the asset is bought at the $t+1$ opening price and held until a sell signal is generated on day $t+s$ ($h_{t+s}^m < \kappa_{80,t+s-1}$).

Next we deploy the short-only strategy called $Bottom20$ where the asset is shorted at the opening price if the forecasted volatility falls below a recursively updated low-volatility threshold given by the historical bottom quintile ($h_{t+1}^m < \kappa_{20,t}$). We unwind the trade at the opening price of day $t+s$ when a buy signal is generated, $h_{t+s}^m > \kappa_{20,t+s-1}$. $Top20$ and $Bottom20$ are less noisy and hence, less

[12] 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, often suggested to identify short term trends in prices (see Pring, 2002) combines a weekly and a monthly trend: if the weekly SMA falls below the monthly SMA then a stop-loss (i.e., sell) signal is generated.

trading-intensive strategies than the *Directional* strategy and so SMA filter rules are not warranted. Finally, we deploy a *long-short* strategy which combines *Top20* and *Bottom20*. The above short-only and long-short strategies are mainly feasible for hedge funds that are not subject to regulatory short-selling constrains.

## 4.3 Assessing Trading Profitability

We now describe our framework to asses the economic value of volatility forecasts. For each trading strategy, the effectiveness of three conditioning information sets (intraday returns, overnight returns and trading volume) is gauged by means of *incremental* profitability; henceforth, the term "incremental" refers to the economic value of augmented-GARCH forecasts over and above that of standard daily return-based GARCH forecasts. In order to account for risk in a way that is robust to non-normality of the strategies' returns, we focus on two metrics: Sortino ratio ($SoR$) and Leland's alpha ($\alpha$). The incremental Sortino ratio (denoted $\Delta SoR$) ranks the competing forecasts on the basis of annualized returns in excess of the risk-free rate per unit of downside risk relative to a 0% target return. Leland (1999) proposes an adjustment to the standard Jensen's (CAPM) alpha to account for nonlinearity of returns relative to the market. It is based on the modified beta estimator

$$\hat{B}_i = \frac{cov(r_{t,i}, -(1+r_{t,M})^{-\hat{b}})}{cov(r_{t,M}, -(1+r_{t,M})^{-\hat{b}})} \tag{3}$$

where $r_{t,i}$ are the daily returns of a trading strategy, $r_{t,M}$ are the market returns (S&P500 proxy) and $b$ represents the exponent of the marginal utility function of the average investor estimated by $\hat{b} = \frac{\ln(\overline{1+r_{t,M}}) - \ln(\overline{1+r_{t,F}}))}{var(\ln(1+r_{t,M}))}$. Leland's alpha follows from the conventional expression $\hat{A}_i = \overline{r_{t,i} - r_{t,F}} - \hat{B}_i(\overline{r_{t,M} - r_{t,F}})$.

We also assess the economic value of predictability by determining the maximum performance fee that a risk-averse investor would be willing to pay to switch between forecasts; see e.g. Fleming et al. (2003), and Della Corte et al. (2010). More specifically, it is assumed that the investor has a quadratic utility function given by

$$U(r_{t,i}) = W_0(1 + r_{t,i} - \frac{\gamma}{2(1+\gamma)}(1 + r_{t,i})^2) \tag{4}$$

where $W_0$ is initial wealth, and $\gamma$ is the investor's degree of relative risk aversion. We compute the maximum amount ($\Phi_\gamma$) that the representative investor is willing to pay to switch from the standard or baseline GARCH forecasts (denoted *base*) to each of the augmented-GARCH forecasts (denoted $i$) by solving the equation

$$\sum_{t=1}^{500} U(r_{t,base}) = \sum_{t=1}^{500} U(r_{t,i} - \Phi_{\gamma,i}). \tag{5}$$

for low and high risk aversion levels $\gamma = \{1, 10\}$ as in Fleming et al. (2003).

Lastly, the economic value of forecasts is assessed in terms of net profitability. The average transaction costs on large stocks for a U.S. institutional investor are estimated to range between 25-31 basis points (bp) per trade by Peterson and Sirri (2003) and Bessembinder (2003); for our individual stock trading simulations a flat $\tau = 28$bp cost per trade is adopted to compute net $SoR$, Leland's $\alpha$ and switching fees. Portfolio trading using the S&P500 index can be easily replicated with ETFs (e.g., SPDR) for which the costs per trade on the US market are estimated much lower at 8-11bp.[13] A flat $\tau = 10$bp is adopted for our index trading simulations.

# 5 Empirical Findings

## 5.1 Individual Stock Trading

By deploying the trading strategies on the sample of stocks, a total of 70 stock-strategy settings (or competitions) among volatility forecasting models are on hand.

[13]Elkins-McSherry Report, Vol.II (2), May 2005, available at *www.elkinsmcsherry.com.*

Table 3 reports the incremental Sortino ratio ($\Delta SoR$) and incremental Leland's alpha ($\Delta\alpha$) of each augmented-GARCH model vis-à-vis the standard GARCH.

[Table 3 around here]

A pervasive finding across stock-strategy settings (in 58 out of 70) is that incremental risk-adjusted profitability can be extracted from augmenting the standard daily GARCH model with additional information. Overall, the predictive ability of *trading volume* stands out with 43% of wins (in those 58 competitions) as suggested by the largest incremental gains in either $\Delta SoR$ or $\Delta\alpha$, followed by *overnight returns* with 31% of wins; the remaining 26% of wins pertain to *intraday returns*.[14] For any given strategy, the information content in trading volume for short-term volatility prediction appears at least as beneficial as that in intraday or overnight returns. To illustrate, for the *Directional SMA-DCMA* strategy the most substantial improvements (i.e., largest $\Delta SoR > 0$ or $\Delta\alpha > 0$) are associated with volume for 4 stocks, with overnight returns for another 4 stocks and with intraday returns (RPV) for 3 stocks; for the *Long-Short* strategy the largest gains are associated with volume in 7 stocks, RPV in 3 stocks and overnight returns in 2 stocks.[15]

The number of trading signals over the 500-day simulation window (on average across stocks) are plotted in Figure 1 for each forecasting model-strategy pair.

[14] Out of 70 settings, only a handful of them show a discrepancy between the $SoR$ and $\alpha$ metrics. In those few exceptions, we proceed by following the metric with the largest incremental gain. For instance, for IBM stock and the *Directional*-SMA-DCMA strategy, GARCH-VOL is best according to $\alpha$ and GARCH-RPV according to $SoR$ but the incremental gain (vis-à-vis the standard daily-based GARCH model) in $\alpha$ exceeds that in $SoR$; hence, we count GARCH-VOL as winner.

[15] For completeness, we computed incremental end-of-period values, incremental annualized returns and standard deviation of returns generated by actively investing \$100 over the holdout period on the basis of augmented GARCH model forecasts. The different information sets afford positive incremental returns that range from 0.2% to 24.1% per annum; trading volume remains in the lead. See Appendix A3 in the working paper version of this article (Fuertes et al., 2013).

[Figure 1 around here]

*Directional* strategies are the most trade intensive with up to 78 roundtrip buy-sell trades on average, whereas *Top20* and *Bottom20* which impose a volatility threshold trading rule are the least trade intensive with 28 trades maximum. Trading intensity is also influenced by the volatility forecasting models; e.g., for the *Top20* strategy where trades are triggered by large forecasted volatilities, the most intense trading corresponds to GARCH-VOL and the least intense to GARCH. This is in line with extant evidence that GARCH-VOL forecasts tend to be biased upwards and GARCH forecasts downwards (Fuertes et al., 2009).

$SoR$ and Leland's $\alpha$ decrease when transaction costs are included but their incremental values vis-à-vis the standard GARCH model can increase or decrease because the different models entail different frequency-of-trading patterns. The incremental Sortino ratio and Leland's $\alpha$ net of trading costs are set out in Table 4.

[Table 4 around here]

The net profitability measures suggest in most of the competitions (i.e., 56 of 70 stock-strategy pairs) that the use of intraday, overnight or volume information is warranted. The ranking of information through win counts (i.e., largest $\Delta NSoR > 0$ or $\Delta N\alpha > 0$) indicates that VOL with 44.6% of wins remains in the lead followed by OVN with 42.9% while the remaining 12.5% pertains to RPV. The gains from conditioning the volatility forecasts on additional information (beyond daily historical returns) can be substantial. With the *Top20* strategy, for instance, the positive incremental net Leland's $\alpha$ ranges between 0.02% and 15.13%, averaging 3.32%, and the incremental net Sortino ranges between 0.003 and 2.74, averaging 0.78.

The economic value of forecasts is gauged next through utility-matching annualized performance fees $\Phi_\gamma$. Table 5 sets out the results.

[Table 5 around here]

Out of the 70 stock-strategy competitions, in a majority of 58 there are positive switching fees for several of the augmented models. Once again, historical daily volume is the best information set leading to the highest performance fees in 40% of the 58 competitions followed by overnight returns with 36% of wins; the remaining 24% corresponds to intraday price information.[16] The predictive value of additional information over and above historical daily returns can be substantial: for the *Top20* strategy the positive switching fees for low (high) relative risk aversion levels vary from 0.01% (0.03%) to 16.81% (10.72%) per annum, averaging 3.46% (3.09%) across stocks. In terms of the size of switching fees and robustness of findings across trading strategies, lagged volume emerges as an excellent GARCH augmentation covariate for trading purposes. The same conclusions are reached when transaction costs are factored in; detailed net performance fees can be found in Appendix A4 of the working paper version of this article (see Fuertes et al., 2013).

While the main goal of the paper is not to propose a “best” trading rule but instead to assess the 1-day-ahead volatility forecasting ability of three information sets in the context of various intuitive trading rules, as a byproduct we comment on the relative performance of the latter. Untabulated results reveal that among the 70 stock-strategy competitions the net $SoR$ exceeds that of the Buy-and-Hold (B&H) in about half of them (i.e., 31 out of 70). Moreover, in 63 out of 70 stock-strategy competitions a risk-averse investor would be willing to pay a relatively high fee after transaction costs to switch from the B&H strategy to an active strategy. The unreported Sortino ratio of the B&H hovers between -0.73 and 1.39 across stocks averaging 0.23. The largest gains in net $SoR$, Leland's $\alpha$ and $\Phi_{\gamma=10}$ versus the B&H

[16] In each stock-strategy competition reported in Table 5 the best information set is defined as the one leading to the highest switching fees for risk aversion parameter $\gamma = 1$ or $\gamma = 10$.

pertain to the *Top20* strategy; the net *SoR* of *Top20* hovers between -0.56 to 8.97 across stocks and volatility forecasting models, averaging 0.38. The average net *SoR* of all other trading rules is below that of the B&H. *Top20* yields average net positive switching fees vis-à-vis the B&H of 9.04% and 91.15% for high ($\gamma = 1$) and low ($\gamma = 10$) risk aversion levels, respectively, the largest across all five strategies. *Top20* is able to outperform B&H in 11 out of 14 stocks based on net *SoR*, in 8 out of 14 stocks based on net $\alpha$, and in 9 out of 14 stocks based on switching fees.[17]

## 5.2 Portfolio Trading

Next we generate volatility forecasts for a well-diversified equity portfolio by fitting model (2) to S&P500 index data. Table 6 sets out the trading results.

[Table 6 around here]

The results suggest that GARCH-VOL forecasts are the most effective index-trading signals. Consistently across the five trading strategies and according to all profitability criteria, both before (Panel A) and after (Panel B) transaction costs, the empirical evidence endorses the common practice by traders of employing volume information as signal for making buy/sell decisions (Pring, 2002).

Across all trading strategies, the annualized utility-based net performance fees shown in Table 6 suggest that volume information (VOL) is very useful for short-term volatility prediction; investors are willing to pay sizeable net fees to switch from standard GARCH to GARCH-VOL forecasts, ranging from 1.49% to 8.36% ($\Phi_{\gamma=1}$) and from 1.27% to 6.87% ($\Phi_{\gamma=10}$). Some gains are afforded by intraday return (RPV) and overnight return (OVN) information, however, they are smaller than those associated to VOL and confined to the least profitable *Directional* strategy.

[17] More detailed results on the comparison of the strategies with the B&H can be found in Appendix A4 of the working paper version of this article (Fuertes et al., 2013).

## 5.3 Statistical versus Economic Value of Volatility Forecasts

On the one hand, our analysis of economic value of volatility forecasts, summarized in Tables 3 to 6, essentially has suggested that augmenting a standard GARCH model with lagged trading volume as regressor can rather effectively enhance the risk- and cost-adjusted trading performance of technical trading strategies. On the other hand, the statistical loss functions summarized in Table 1 advocate instead the intraday return-based RPV as the most useful augmentation variable since it leads to the largest improvement in statistical forecast accuracy.[18] Hence, the analysis reveals a disconnect between statistical significance and economic value of predictability.

In order to shed further light on this disconnect we gauge the degree of association between the model rankings arising from common statistical forecast accuracy metrics (e.g., MSE) and profitability metrics (e.g., alpha). Figure 2 shows scatterplots and rank correlations.[19] We report results only for the *Top20* strategy, to save space, given the qualitatively similar outcomes from the other strategies.

[Figure 2 around here]

On the top-right corner of each graph we report the Kendall's *tau*, a rank-correlation measure of (non)linear association between variables.[20] The graphs illustrate strong rank correlations between different profitability measures: Leland's

[18] We computed the statistical criteria reported in Table 1 separately over high volatility (top quintile) and low volatility (bottom quintile) out-of-sample days. RPV remains in the lead from the point of view of statistical accuracy for extremely low and high volatility days. Conversely, trading volume incurs poor statistical forecast accuracy especially for extreme volatility days.

[19] Each graph contains $60 = 4 \times 15$ observations corresponding to four models (standard GARCH and three augmented versions) and fifteen assets (14 individual stocks and S&P500 portfolio).

[20] Kendall's *tau* is based on the number of concordances and discordances between the variables. If the number of concordances and discordances are roughly the same for all observations, there is no association between the variables. Relatively large numbers of concordances (discordances) suggest a positive (negative) relationship between the variables.

$\alpha$ versus the $SoR$ (0.767; $p$-value = 0.000) and performance fees $\Phi_{\gamma=10}$ versus Leland's $\alpha$ (0.415; $p$-value = 0.001). The graphs corroborate that the MSE may not capture well the economic value of predictability to investors. The correlations between forecast rankings from profitability measures and MSE are very small. For instance, Kendall's *tau* between MSE and Sortino ratio is insignificant at -0.002 ($p$-value 0.985), and likewise between MSE and Leland's $\alpha$ (0.034; $p$-value 0.707).[21] The disconnect between statistical accuracy and profitability of volatility forecasts here illustrated highlights the importance of using appropriate metrics that reflect the purpose for which the volatility forecasts are intended.[22]

# 6 Conclusions

Forecasting stock market volatility has been the subject of extensive empirical research. Recent studies have advocated the use of realized volatility measures constructed from intraday prices as a way to enhance the statistical accuracy of standard daily return-based GARCH predictions. Volume information has proven, in contrast, rather unsuccessful for volatility prediction. There is mixed evidence regarding the predictive content in overnight returns for the subsequent daytime volatility. Most extant research on these issues has solely relied on statistical loss functions such as those implicit in Mean Square Error or Mean Absolute Error criteria while the economic relevance of predictability has received relatively scant attention. In the present paper we deploy various volatility-based technical trading rules in order to

[21] Similar findings emerge from rank correlation measures and scatterplots using the remaining statistical loss functions reported in Table 1 instead of the MSE. Details available upon request.

[22] This disconnect has been documented in other contexts. Abhyankar et al. (2005) show that a utility-based value approach reverses the previous empirical consensus that monetary-fundamental models cannot beat the random walk. Hall and Sirichand (2010) compare the forecast performance of an atheoretic and a theory-informed model of bond returns for portfolio decision making and illustrate the sensitivity of the ranking to the evaluation criteria.

assess the economic significance of augmenting the standard GARCH model with realized volatilities, trading volume or overnight returns. The trading strategies are deployed separately for 14 individual large-cap US stocks and for the S&P500 index.

One finding that permeates through both statistical and economic loss functions is the relevance of exploiting additional information, over and above historical daily returns, for daily volatility forecasting. Another important finding is the lack of correlation between statistical significance and economic value of forecasts, namely, our analysis suggests that de facto statistical metrics such as the Mean Square Error and Mean Absolute Error may be of little value to practitioners. Realized volatilities stand out as the most efficient predictor from the point of view of statistical loss functions. The merit of volume as predictor of future volatility is not apparent in the statistical framework but profitability criteria such as the Sortino ratio and Leland's alpha, before and after trading costs, endorse investors' common practice of using volume as trading indicator. As a byproduct, our research reveals a stronger daily return-volatility nexus in turbulent periods. Echoing this finding the best trading rule buys the asset when its volatility forecast exceeds the historical top quintile.

In future research, it would be interesting to assess if these conclusions hold in different volatility-based trading settings such as variance swaps or options trading. Further, following Wu and Xu (2000) who document that trades on NYSE are more informative than those on other exchanges such as NASDAQ, it might be interesting to reassess their evidence using the methodology employed in the present paper.

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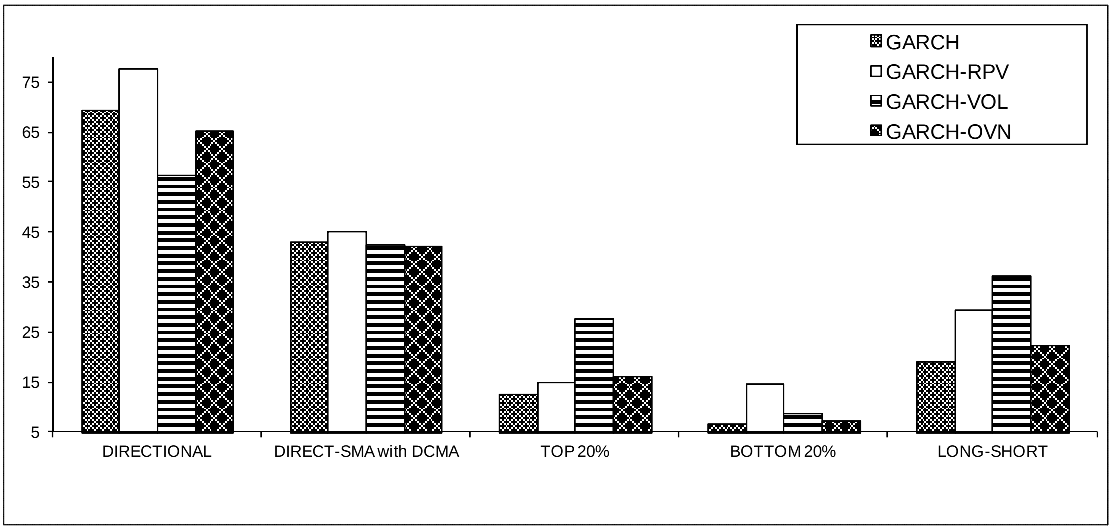


**Figure 1. Average number of trading signals.** The bar chart provides, for each volatility forecasting model and trading strategy pair, the number of roundtrip buy-sell trading signals triggered during the 500-day out-of-sample period on average across stocks.

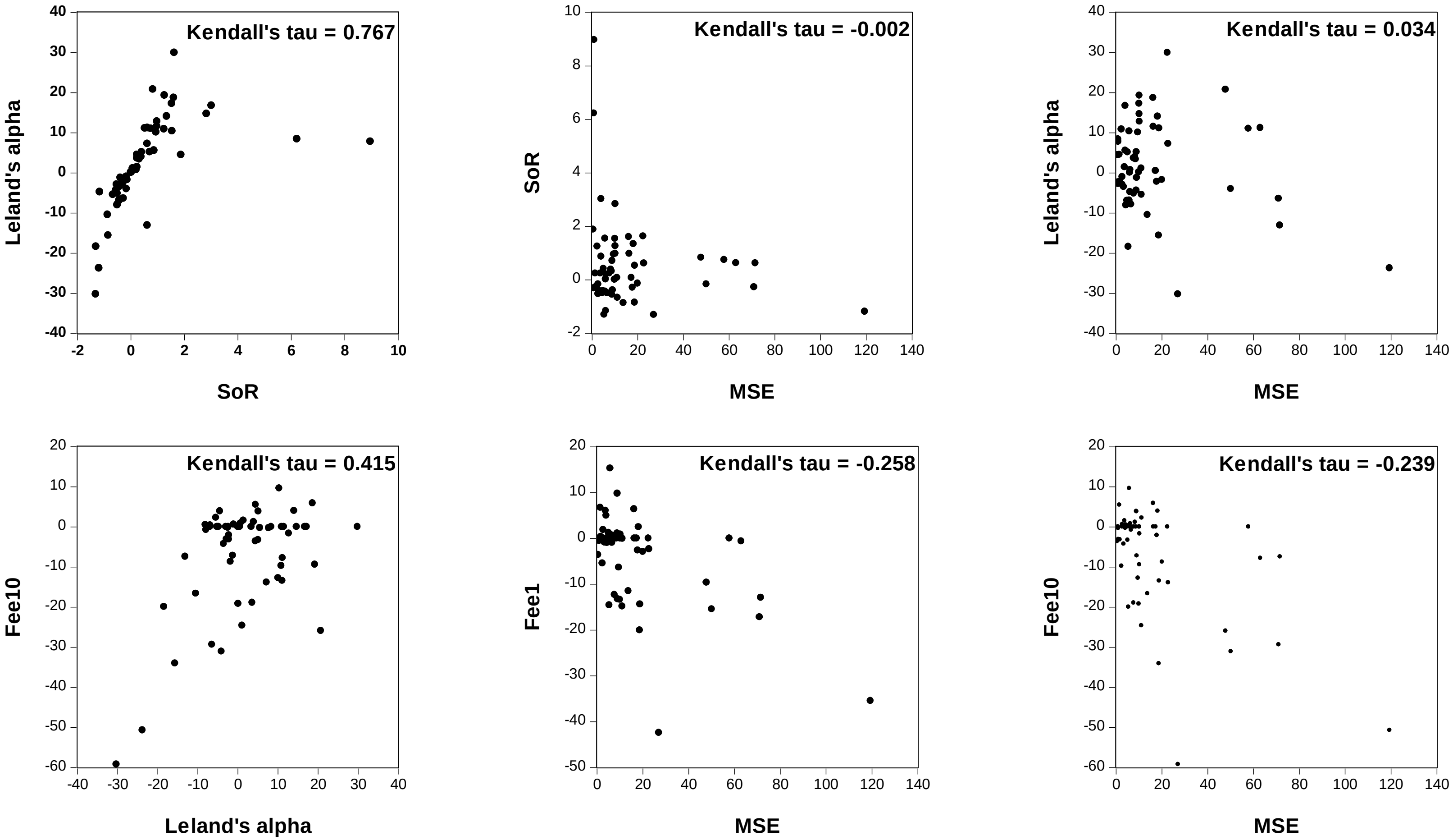


**Figure 2. Ranking of volatility forecasts by profitability of Top20 trading strategy vis-à-vis statistical accuracy.** The scatterplots show the degree of association between Mean Squared Error (MSE) and the profitability measures: Leland's alpha, Sortino ratio (*SoR*), performance fees (%) that an investor with quadratic utility and constant relative risk aversion of $\gamma=\{1,10\}$ would be willing to pay to switch from using only daily return data (baseline GARCH forecasts) to using additional information (augmented GARCH forecasts). Each graph has 60 points corresponding to four models (standard GARCH and augmented versions) and fifteen assets (14 individual stocks and S&P500 portfolio). In the top-right corner of each graph we report the Kendall's *tau* rank correlation measure.

## Table 1. Statistical forecast evaluation of volatility forecasts.

| | Statistical Criteria | | | | | | | | Tests | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Model** | MSE | MAE | HMSE | AMAPE | MME(U) | MME(O) | GMLE | MZ-$R^2$ | ENC-T | PT-T |
| *Financial stock: American Express (AXP)* | | | | | | | | | | |
| GARCH | 16.406* | 2.082* | 1.939** | 0.257*** | 49.342* | 7.715 | 2.211** | 29.044* | — | 4.621*** |
| GARCH-RPV | 10.321 | 1.666 | 0.828 | 0.211 | 29.614 | 5.615 | 2.129 | 56.967 | 4.158*** | 3.451*** |
| GARCH-VOL | 18.239*** | 2.305*** | 38.958*** | 0.271*** | 49.766*** | 10.330*** | 2.255*** | 22.240** | -1.613 | 4.717*** |
| GARCH-OVN | 16.222*** | 2.067*** | 1.914*** | 0.255** | 49.199*** | 7.510 | 2.207*** | 29.802* | 2.119** | 5.507*** |
| *Industrial stock: Caterpillar (CAT)* | | | | | | | | | | |
| GARCH | 6.141*** | 1.780*** | 1.833*** | 0.281*** | 16.810** | 5.751*** | 2.068*** | 13.986* | — | 4.097*** |
| GARCH-RPV | 3.806 | 1.288 | 0.845 | 0.217 | 12.008 | 3.681 | 1.985 | 43.640 | 7.719*** | 4.355*** |
| GARCH-VOL | 8.984*** | 2.215*** | 4.688*** | 0.312*** | 19.946** | 9.264*** | 2.129*** | 4.986*** | -3.923 | 4.441*** |
| GARCH-OVN | 5.825*** | 1.539** | 1.515*** | 0.247*** | 11.882* | 6.121*** | 2.030* | 23.554* | 3.121*** | 5.006*** |
| *Technology stock: Microsoft (MSFT)* | | | | | | | | | | |
| GARCH | 8.611** | 1.952*** | 1.282*** | 0.252** | 19.606* | 8.488*** | 2.224*** | 35.520* | — | 5.724*** |
| GARCH-RPV | 5.132 | 1.515 | 0.689 | 0.205 | 10.316 | 5.464 | 2.169 | 58.156 | 5.087*** | 4.472*** |
| GARCH-VOL | 18.688*** | 3.425*** | 5.187*** | 0.349*** | 22.864** | 21.144*** | 2.356*** | 16.830** | -1.338 | 3.220*** |
| GARCH-OVN | 8.373*** | 1.942*** | 1.322*** | 0.252*** | 17.493* | 8.307*** | 2.226*** | 34.614* | 2.475*** | 6.082*** |
| *Index: Standard & Poor's 500 (S&P500)* | | | | | | | | | | |
| GARCH | 0.954*** | 0.672 | 2.088 | 0.259 | 3.300* | 1.517 | 1.101 | 53.804 | — | 4.618*** |
| GARCH-RPV | 0.775 | 0.607 | 0.945 | 0.225 | 1.953 | 1.255 | 1.062 | 63.577 | 4.608*** | 5.334*** |
| GARCH-VOL | 1.525** | 0.887** | 6.905*** | 0.311** | 4.597** | 2.160*** | 1.255** | 30.613** | -3.299 | 4.173*** |
| GARCH-OVN | 1.024* | 0.693** | 1.566* | 0.254*** | 3.236* | 1.637* | 1.086** | 53.571 | -0.309 | 4.265*** |

The table reports the estimated expected forecast error losses for the standard daily GARCH model and extensions using lagged realized power variation (RPV), trading volume (VOL) or squared overnight returns (OVN) as augmentation variable $\nu_{t-1}$ in Eq. (2). Bold indicates the top performer. *, **, *** denote significantly larger losses than those of the top performer (Diebold-Mariano test) at the 10%, 5% or 1% level. The last two columns report the encompassing test of Harvey et al. (1998; ENC-T) developed for the MSE loss function, and the non-parametric market timing test of Pesaran and Timmermann (1992; PT-T). Asterisks for the ENC-T test indicate that the forecasts from the corresponding augmented-GARCH model add significant information to those from the standard GARCH model. Asterisks for the PT-T test indicate that there is significant dependence between the directional change forecasts and realizations.

**Table 2. Contemporaneous return-volatility relationship.**

| | sample size | A. Pooled OLS model | | | B. Random Effects model | | | |
|---|---|---|---|---|---|---|---|---|
| | $N \times T_0$ | Correl($r_t$,$\sigma_t^2$) | Slope | $t$-statistic | $R^2$ | Slope | $t$-statistic | Hausman test |
| overall sample | 17654 | 3.343% | 0.015 | **3.671** | 0.110% | 0.015 | **3.648** | 0.858 |
| Q1 (high volatility) | 3528 | 8.588% | 0.038 | **4.103** | 0.738% | 0.038 | **4.103** | 0.070 |
| Q2 | 3528 | -4.751% | -0.056 | -2.267 | 0.128% | -0.054 | -1.714 | 0.612 |
| Q3 | 3528 | 0.989% | 0.015 | 0.424 | 0.001% | -0.005 | -0.106 | 0.024 |
| Q4 | 3528 | 3.730% | 0.070 | **2.592** | 0.057% | 0.060 | **2.027** | 0.236 |
| Q5 (low volatility) | 3528 | 5.818% | 0.111 | **2.740** | 0.141% | 0.093 | **1.826** | 0.310 |

The dependent variable is the daily return and the regressor is the daily realized variance over the in-sample period pooled across the 14 stocks. $Q_1$ to $Q_5$ are the sample quintiles of the realized variance. Exhibit A reports POLS estimation results where the correlation between daily returns and daily realized variance is given by the $(R^2)^{1/2}$ of the panel regression. Exhibit B reports the Random Effects estimation results and *p*-value of the Hausman test to confront Random Effects and Fixed Effects specifications; *p*-values below 0.05 indicate that a Fixed Effects specification is more appropriate. Bold denotes a significantly positive relationship at the 10%, 5% or 1% level. Reported *t*-statistics are based on a covariance estimator that is robust to contemporaneous correlation across stocks as well as different error variances.

**Table 3. Risk-adjusted performance evaluation: stock trading.**

| | | Trading strategy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Directional | | Directional SMA-DCMA | | Top20 | | Bottom20 | | Long-Short | |
| **Stock** | $v_{t-1}$ | *ΔSoR* | $\Delta\alpha$ | *ΔSoR* | $\Delta\alpha$ | *ΔSoR* | $\Delta\alpha$ | *ΔSoR* | $\Delta\alpha$ | *ΔSoR* | $\Delta\alpha$ |
| ATT | RPV | -0.16 | -8.71 | -0.55 | -6.39 | -1.06 | -16.62 | -0.16 | -0.50 | -1.10 | -17.22 |
| | VOL | -0.17 | -8.94 | -0.17 | -18.40 | -0.62 | -1.52 | ***17.21*** | ***2.58*** | -0.48 | ***2.01*** |
| | OVN | -0.05 | -2.30 | -0.08 | -0.77 | -0.90 | -13.40 | -0.58 | -2.01 | -0.25 | -2.28 |
| AXP | RPV | -0.12 | -2.37 | ***0.01*** | -0.38 | **0.24** | **4.37** | -0.61 | -4.89 | -0.23 | -1.96 |
| | VOL | ***0.13*** | ***2.37*** | -0.11 | -1.18 | ***0.65*** | **5.06** | ***0.67*** | ***3.14*** | ***0.88*** | ***8.64*** |
| | OVN | **0.06** | **1.01** | -0.26 | -2.54 | **0.63** | ***7.10*** | -0.47 | -2.62 | **0.26** | **3.26** |
| BA | RPV | **0.09** | **1.61** | **0.21** | **2.07** | -0.84 | -11.92 | -0.56 | -2.09 | -0.90 | -13.59 |
| | VOL | **0.79** | **11.57** | **0.36** | **3.15** | ***0.76*** | ***6.04*** | N/A | ***2.36*** | ***1.02*** | ***8.44*** |
| | OVN | ***1.41*** | ***17.72*** | ***0.84*** | ***6.95*** | **0.42** | **3.33** | ***0.07*** | **0.59** | **0.42** | **3.89** |
| CAT | RPV | -0.15 | -2.11 | -0.37 | -4.08 | **0.58** | **4.17** | -0.16 | -3.69 | **0.25** | **0.15** |
| | VOL | ***1.41*** | ***23.74*** | ***0.49*** | ***5.28*** | ***2.60*** | ***17.68*** | N/A | ***3.85*** | ***3.54*** | ***21.68*** |
| | OVN | -0.12 | -2.07 | -0.25 | -2.90 | **1.64** | **11.83** | N/A | **3.24** | **2.47** | **15.10** |
| DELL | RPV | ***0.19*** | ***6.08*** | -0.31 | -3.01 | -3.00 | -13.63 | -0.76 | -6.89 | -2.00 | -20.43 |
| | VOL | -0.44 | -7.68 | -0.32 | -3.08 | -4.10 | -33.42 | -0.84 | -7.59 | -2.74 | -39.01 |
| | OVN | -0.29 | -6.21 | -0.31 | -2.99 | -3.46 | -17.31 | -0.24 | -2.58 | -2.15 | -19.49 |
| GE | RPV | 0.00 | -0.10 | -0.25 | -1.86 | -1.34 | -12.76 | ***0.63*** | ***2.26*** | -0.98 | -9.88 |
| | VOL | **0.04** | **1.02** | **0.10** | **0.79** | -0.01 | ***7.06*** | -0.21 | -1.14 | ***0.01*** | ***5.36*** |
| | OVN | ***1.06*** | ***19.21*** | ***1.07*** | ***6.79*** | -1.44 | -13.90 | **0.07** | **2.12** | -1.06 | -11.16 |
| GM | RPV | -0.15 | -2.19 | ***0.43*** | ***2.56*** | -0.01 | -0.08 | -0.09 | -1.46 | -0.09 | -1.46 |
| | VOL | -0.98 | -18.54 | -0.84 | -7.99 | **0.13** | **2.25** | -0.87 | -11.78 | -0.51 | -9.33 |
| | OVN | ***0.02*** | ***0.57*** | -0.17 | -1.34 | ***0.15*** | ***2.55*** | ***0.17*** | ***0.52*** | ***0.17*** | ***2.96*** |
| IBM | RPV | ***0.60*** | ***12.95*** | ***0.14*** | **1.18** | -2.32 | -7.34 | -0.49 | -4.07 | -1.89 | -11.72 |
| | VOL | **0.34** | **6.18** | **0.10** | ***1.34*** | -4.74 | -40.85 | ***0.90*** | ***3.54*** | -3.25 | -36.72 |
| | OVN | **0.06** | **1.32** | 0.00 | 0.00 | -1.51 | ***3.19*** | **0.24** | **1.11** | -0.48 | ***4.47*** |
| JPM | RPV | **0.52** | **11.39** | ***0.66*** | **6.16** | -1.24 | -18.22 | -0.45 | -6.67 | -1.32 | -24.30 |
| | VOL | **0.41** | **9.60** | **0.21** | **2.55** | ***0.09*** | ***5.30*** | **-0.20** | **0.15** | ***0.16*** | ***5.33*** |
| | OVN | ***0.72*** | ***16.66*** | **0.52** | ***6.29*** | -1.35 | -20.69 | ***0.62*** | ***2.77*** | -1.07 | -17.36 |
| KO | RPV | -0.05 | -0.12 | -0.73 | -4.44 | ***0.19*** | ***1.28*** | ***0.47*** | ***2.38*** | ***0.55*** | ***3.60*** |
| | VOL | -0.15 | -1.33 | -0.61 | -3.54 | -0.01 | -0.28 | -0.56 | -3.10 | -0.16 | -3.34 |
| | OVN | ***0.39*** | ***3.79*** | -0.04 | -0.15 | **0.19** | **1.13** | **0.34** | **1.95** | **0.42** | **3.02** |
| MCD | RPV | -0.26 | -5.25 | **0.09** | **0.82** | -1.34 | -10.15 | -0.97 | -7.65 | -1.64 | -17.55 |
| | VOL | ***0.98*** | ***12.91*** | ***0.85*** | ***6.63*** | -0.25 | -1.74 | ***0.86*** | ***4.15*** | ***0.26*** | ***2.69*** |
| | OVN | -0.36 | -3.47 | -0.50 | -4.76 | -0.68 | -2.16 | N/A | **1.00** | -0.38 | -1.07 |
| MSF | RPV | -0.20 | -4.46 | -0.15 | -1.61 | ***0.15*** | ***3.03*** | ***1.60*** | ***4.58*** | ***0.54*** | ***7.97*** |
| | VOL | -0.09 | -3.00 | -0.18 | -3.28 | -0.84 | -10.07 | **0.27** | **1.64** | -0.58 | -8.13 |
| | OVN | ***0.35*** | ***6.78*** | ***0.06*** | ***0.92*** | **0.05** | **0.32** | -0.15 | -0.98 | -0.07 | -0.75 |
| PG | RPV | -0.65 | -6.22 | 0.00 | ***0.56*** | -4.54 | -3.36 | ***0.56*** | ***3.39*** | -0.26 | -0.15 |
| | VOL | -0.15 | ***1.33*** | -0.44 | -3.19 | -6.24 | -0.85 | -0.89 | -1.72 | -0.78 | -3.13 |
| | OVN | -0.03 | -0.23 | -0.40 | -2.12 | 3.94 | -0.01 | -0.74 | -3.49 | -0.67 | -4.24 |
| WMT | RPV | -1.04 | -15.93 | **0.03** | **0.54** | ***0.78*** | ***5.55*** | -0.64 | -3.94 | -0.09 | ***1.78*** |
| | VOL | -0.66 | -8.58 | ***0.33*** | ***3.77*** | **0.12** | **0.40** | -0.97 | -6.71 | -0.84 | -6.37 |
| | OVN | -0.22 | -3.27 | -0.06 | -0.63 | **0.01** | **0.02** | ***0.11*** | ***0.72*** | ***0.10*** | **0.75** |

The table reports the incremental annualized Sortino ratio (Δ*SoR*) and Leland's alpha (Δα%) of augmented-GARCH forecasts relative to standard GARCH forecasts. The augmentation variable, $\nu_{t-1}$ in Eq. (1b), is realized power variation (RPV), trading volume (VOL) or the squared overnight return (OVN). Bold indicates that the augmented-GARCH forecast entails a gain relative to the GARCH forecast. For each stock-strategy pair, italics font denotes the forecasting model that provides the largest gain. N/A indicates that *SoR* cannot be computed because there are very few trades and the investor holds instead the risk free rate over most of the out-of-sample period so all the returns are positive.

**Table 4. Net risk-adjusted performance evaluation: stock trading.**

| | | **Trading strategy** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Directional | | Directional SMA-DCMA | | Top20 | | Bottom20 | | Long-short | |
| **Stock** | $v_{t-1}$ | *ΔNSoR* | $\Delta N\alpha$ | *ΔNSoR* | $\Delta N\alpha$ | *ΔNSoR* | $\Delta N\alpha$ | *ΔNSoR* | $\Delta N\alpha$ | *ΔNSoR* | $\Delta N\alpha$ |
| ATT | RPV | -0.15 | -8.66 | -0.57 | -7.87 | -1.10 | -18.80 | -0.76 | -2.72 | -1.25 | -21.82 |
| | VOL | -0.12 | -6.55 | ***0.47*** | -15.92 | -0.80 | -9.16 | ***6.28*** | ***2.01*** | -0.69 | -6.39 |
| | OVN | -0.07 | -3.28 | -0.05 | -0.46 | -1.00 | -43.01 | -0.70 | -2.57 | -0.47 | -7.10 |
| AXP | RPV | -0.34 | -2.24 | -0.02 | -1.21 | **0.003** | **1.23** | -0.64 | -5.85 | -0.44 | -5.40 |
| | VOL | -0.19 | ***1.77*** | -0.10 | -1.46 | **0.36** | **2.53** | ***0.33*** | ***1.71*** | ***0.57*** | ***5.82*** |
| | OVN | -0.34 | -0.54 | -0.23 | -2.86 | ***0.63*** | ***7.15*** | -0.56 | -3.37 | **0.22** | **2.86** |
| BA | RPV | **0.27** | **3.13** | **0.35** | **3.37** | -0.80 | -13.26 | -0.82 | -3.42 | -0.90 | -15.76 |
| | VOL | ***1.16*** | ***17.55*** | **0.54** | **5.66** | -0.16 | -0.29 | ***4.18*** | ***2.91*** | ***0.07*** | ***2.47*** |
| | OVN | **1.06** | **16.31** | ***0.76*** | ***7.99*** | -0.05 | ***0.73*** | -0.01 | **0.58** | -0.05 | **1.27** |
| CAT | RPV | -0.16 | -3.15 | -0.40 | -4.97 | **1.40** | **6.19** | -0.41 | -5.22 | **0.73** | **0.66** |
| | VOL | ***1.27*** | ***22.07*** | ***0.40*** | ***5.15*** | **1.88** | **9.94** | ***3.06*** | ***4.11*** | **2.45** | **13.89** |
| | OVN | -0.25 | -4.43 | -0.21 | -3.25 | ***2.71*** | ***15.13*** | N/A | **3.78** | ***3.24*** | ***18.73*** |
| DELL | RPV | ***0.75*** | ***16.80*** | -0.24 | -3.35 | -2.83 | -14.55 | -0.82 | -8.38 | -1.82 | -22.15 |
| | VOL | -0.18 | -4.64 | -0.31 | -3.54 | -4.02 | -38.44 | -1.01 | -10.00 | -2.46 | -42.24 |
| | OVN | -0.33 | -6.53 | -0.30 | -3.21 | -3.22 | -15.91 | -0.22 | -3.01 | -1.92 | -18.03 |
| GE | RPV | -0.17 | -2.86 | -0.11 | -1.17 | -1.29 | -13.58 | ***0.50*** | **1.42** | -0.98 | -11.56 |
| | VOL | **0.39** | **5.96** | **0.05** | **0.19** | -0.27 | ***2.06*** | -0.19 | -1.13 | -0.22 | ***0.62*** |
| | OVN | ***1.00*** | ***17.36*** | ***0.82*** | ***6.95*** | -1.46 | -16.12 | -0.11 | ***1.83*** | -1.11 | -13.62 |
| GM | RPV | -0.05 | -1.27 | ***0.23*** | ***2.22*** | -0.08 | -1.12 | -0.21 | -2.23 | -0.19 | -3.11 |
| | VOL | -0.74 | -14.73 | -0.61 | -6.40 | -0.01 | ***0.07*** | -0.87 | -12.82 | -0.60 | -11.22 |
| | OVN | ***0.10*** | ***1.82*** | -0.04 | -0.31 | -0.07 | -0.95 | ***0.21*** | ***0.79*** | -0.03 | -0.17 |
| IBM | RPV | **0.42** | ***9.21*** | -0.06 | -0.57 | -1.78 | -5.86 | -0.84 | -6.84 | -1.74 | -13.21 |
| | VOL | ***0.47*** | **9.09** | ***0.12*** | ***0.94*** | -4.34 | -46.97 | **0.02** | ***2.53*** | -2.94 | -42.04 |
| | OVN | **0.06** | **1.37** | **0.00** | **0.00** | -2.07 | -6.64 | ***0.12*** | **0.56** | -1.05 | -5.16 |
| JPM | RPV | -0.04 | -0.60 | **0.11** | **3.80** | -0.91 | -15.03 | -0.56 | -8.81 | -1.04 | -22.82 |
| | VOL | **0.44** | **10.01** | **0.04** | **2.54** | -0.11 | ***0.20*** | -0.32 | -0.12 | -0.05 | ***0.21*** |
| | OVN | ***0.72*** | ***16.83*** | ***0.25*** | ***5.31*** | -1.02 | -17.42 | ***0.42*** | ***1.90*** | -0.76 | -14.86 |
| KO | RPV | -0.19 | -3.21 | -0.46 | -5.15 | **0.26** | **0.69** | -0.08 | -1.32 | **0.27** | -0.65 |
| | VOL | **0.20** | **2.16** | -0.43 | -3.88 | **0.10** | -0.55 | -0.86 | -5.47 | -0.26 | -5.78 |
| | OVN | ***0.37*** | ***5.26*** | ***0.13*** | ***0.77*** | ***0.36*** | ***1.93*** | ***0.27*** | ***1.63*** | ***0.47*** | ***3.38*** |
| MCD | RPV | -0.47 | -7.04 | -0.04 | **0.96** | -0.94 | -10.97 | -1.05 | -10.43 | -1.26 | -19.93 |
| | VOL | ***0.65*** | ***10.53*** | ***0.61*** | ***6.77*** | -0.37 | -2.73 | ***0.29*** | **0.70** | -0.19 | -1.95 |
| | OVN | **0.06** | **0.47** | -0.20 | -3.19 | -0.21 | -2.28 | N/A | ***3.49*** | ***0.21*** | ***1.22*** |
| MSFT | RPV | -0.08 | -2.93 | -0.11 | -1.42 | ***0.09*** | ***1.73*** | ***1.08*** | **1.20** | ***0.23*** | ***2.92*** |
| | VOL | **0.18** | **1.43** | -0.12 | -3.53 | -1.16 | -19.00 | **0.38** | ***2.17*** | -0.85 | -16.35 |
| | OVN | ***0.27*** | ***5.67*** | ***0.02*** | ***0.81*** | **0.06** | **0.60** | -0.15 | -1.24 | -0.07 | -0.72 |
| PG | RPV | -1.65 | -15.41 | -0.36 | -0.23 | -4.34 | -3.94 | ***0.26*** | -0.48 | -0.51 | -4.51 |
| | VOL | ***1.54*** | ***16.05*** | -0.30 | -3.96 | -5.60 | -1.15 | **0.00** | ***4.12*** | ***0.33*** | ***3.10*** |
| | OVN | **0.24** | **2.50** | -0.29 | -2.10 | ***2.74*** | -0.61 | -0.57 | -2.27 | -0.63 | -3.42 |
| WMT | RPV | -0.92 | -16.22 | **0.04** | **0.91** | ***0.85*** | ***5.50*** | -0.62 | -4.66 | -0.05 | ***5.91*** |
| | VOL | -0.66 | -8.14 | ***0.20*** | ***3.55*** | **0.19** | **0.68** | -0.95 | -7.86 | -0.80 | -2.11 |
| | OVN | -0.12 | -1.98 | -0.04 | -0.55 | **0.004** | **0.02** | ***0.10*** | ***0.70*** | ***0.09*** | **5.81** |

The table reports for each augmented-GARCH model the incremental annualized cost-adjusted Sortino Ratio (Δ*NSoR*) and Leland's alpha ($\Delta N\alpha\%$) relative to the standard GARCH model. The augmentation variable, $\nu_{t-1}$ in Eq. (1b), is realized power variation (RPV), trading volume (VOL) or the squared overnight return (OVN). Bold indicates that the augmented-GARCH forecasts entail a gain relative to the GARCH forecasts. For each stock-strategy pair, italics indicates the forecasting model that attains the largest gain. N/A means that *NSoR* cannot be computed because too few trades are triggered and the investor holds the risk free rate over most of the out-of-sample period; hence, all the returns are positive.

**Table 5. Utility-based performance evaluation: stock trading.**

| | | Trading strategy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Directional | | Directional SMA-DCMA | | Top20 | | Bottom20 | | Long-Short | |
| **Stock** | $v_{t-1}$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ |
| ATT | RPV | -13.59 | -17.78 | -6.62 | -6.74 | -11.99 | -11.02 | -0.61 | -1.54 | -12.53 | -12.42 |
| | VOL | -13.41 | -12.83 | -27.01 | -72.14 | -3.86 | -25.63 | ***2.52*** | ***1.92*** | -1.43 | -24.19 |
| | OVN | -3.17 | -0.56 | -0.71 | ***0.02*** | -9.72 | -9.33 | -2.07 | -2.62 | -1.59 | -0.49 |
| AXP | RPV | -2.58 | -4.09 | -0.50 | -1.35 | **3.59** | **0.91** | -5.15 | -6.28 | -2.19 | -5.87 |
| | VOL | ***2.39*** | **1.89** | -1.32 | -1.45 | **4.66** | ***6.33*** | ***3.26*** | ***3.52*** | ***8.07*** | ***10.09*** |
| | OVN | **1.21** | ***2.62*** | -2.82 | -2.82 | ***6.22*** | **5.73** | -2.71 | -2.87 | **2.88** | **2.22** |
| BA | RPV | **1.22** | -1.69 | **1.95** | **1.19** | -14.81 | -21.82 | -2.12 | -2.08 | -14.47 | -19.68 |
| | VOL | **10.80** | **7.12** | **3.06** | **2.69** | ***3.67*** | ***3.75*** | ***2.50*** | ***3.46*** | ***9.00*** | ***12.57*** |
| | OVN | ***17.38*** | ***19.10*** | ***6.89*** | ***7.23*** | **1.07** | **1.71** | **0.64** | **1.02** | **4.33** | **7.75** |
| CAT | RPV | -2.11 | -4.34 | -4.11 | -3.86 | **3.66** | -0.69 | -3.97 | -5.34 | -0.46 | -6.00 |
| | VOL | ***20.74*** | ***18.22*** | ***5.33*** | ***5.00*** | ***16.81*** | ***10.72*** | ***4.01*** | ***4.33*** | ***21.49*** | ***15.52*** |
| | OVN | -1.86 | -2.28 | -3.01 | -3.54 | **11.09** | **5.49** | **3.38** | **3.73** | **14.85** | **9.43** |
| DELL | RPV | ***4.03*** | -6.51 | -3.04 | -3.92 | -12.39 | -18.15 | -7.10 | -7.60 | -18.61 | -24.37 |
| | VOL | -7.81 | -17.96 | -3.00 | -2.95 | -30.69 | -46.77 | -7.82 | -8.38 | -36.11 | -51.19 |
| | OVN | -5.07 | -2.60 | -2.90 | -2.70 | -14.22 | -8.15 | -2.83 | -4.58 | -16.65 | -12.36 |
| GE | RPV | -0.14 | -0.87 | -1.84 | -1.92 | -11.33 | -17.94 | **2.19** | **0.88** | -9.38 | -17.20 |
| | VOL | **0.34** | -5.35 | **0.66** | -0.31 | ***4.66*** | -5.64 | -1.19 | -1.30 | ***3.41*** | -6.88 |
| | OVN | ***17.29*** | ***6.96*** | ***6.62*** | ***6.24*** | -12.67 | -22.57 | ***2.30*** | ***3.26*** | -10.66 | -20.00 |
| GM | RPV | -2.21 | -5.24 | ***2.24*** | ***2.90*** | **0.08** | **1.49** | -1.56 | -1.95 | -1.48 | -0.49 |
| | VOL | -15.77 | -13.76 | -6.65 | -5.68 | **2.40** | **2.59** | -12.54 | -14.82 | -10.44 | -12.60 |
| | OVN | ***0.38*** | -0.63 | -1.16 | -1.34 | ***2.71*** | ***2.94*** | ***0.53*** | ***0.44*** | ***3.26*** | ***3.39*** |
| IBM | RPV | ***16.80*** | ***11.38*** | **1.12** | ***1.16*** | -6.55 | -10.93 | -4.31 | -5.34 | -10.58 | -15.71 |
| | VOL | **7.39** | -0.88 | ***1.15*** | **0.05** | -36.25 | -54.84 | ***3.85*** | ***5.58*** | -33.79 | -52.26 |
| | OVN | **1.66** | **0.49** | **0.00** | **0.00** | ***1.90*** | -4.94 | **1.14** | **1.07** | ***3.06*** | -3.91 |
| JPM | RPV | **11.62** | ***12.48*** | ***6.17*** | ***9.28*** | -17.39 | -32.84 | -7.31 | -11.07 | -23.44 | -40.30 |
| | VOL | **9.14** | **4.31** | **2.38** | **2.15** | ***3.61*** | -4.12 | **0.27** | **1.23** | ***3.89*** | -2.93 |
| | OVN | ***16.13*** | **10.44** | **5.79** | **4.42** | -19.06 | -31.00 | ***2.81*** | ***2.36*** | -16.79 | -29.34 |
| KO | RPV | -0.18 | -0.88 | -4.38 | -4.93 | **0.89** | -2.65 | ***2.45*** | **1.73** | ***3.36*** | -0.96 |
| | VOL | -1.36 | -2.63 | -3.49 | -3.83 | -0.65 | -3.97 | -3.27 | -3.01 | -3.90 | -6.85 |
| | OVN | ***3.55*** | ***5.08*** | -0.15 | -0.10 | ***0.97*** | -0.31 | **2.06** | ***2.00*** | **3.05** | ***1.68*** |
| MCD | RPV | -4.00 | -1.23 | **1.03** | **2.80** | -10.02 | -15.44 | -7.99 | -10.25 | -17.21 | -24.12 |
| | VOL | ***10.80*** | ***12.89*** | ***6.77*** | ***7.46*** | -1.55 | -1.04 | ***4.03*** | **2.57** | ***2.41*** | ***1.51*** |
| | OVN | -3.28 | -7.11 | -4.88 | -5.49 | -2.65 | -8.43 | **1.20** | ***2.88*** | -1.48 | -5.78 |
| MSFT | RPV | -5.39 | -8.48 | -1.83 | -1.78 | ***2.36*** | -2.11 | ***4.50*** | ***2.39*** | ***6.96*** | ***0.25*** |
| | VOL | -4.21 | -11.27 | -3.85 | -4.76 | -11.29 | -26.94 | **1.72** | **1.92** | -9.76 | -25.51 |
| | OVN | ***7.66*** | ***7.61*** | ***1.08*** | ***1.46*** | **0.34** | ***0.91*** | -1.03 | -1.13 | -0.69 | -0.24 |
| PG | RPV | -5.48 | -3.98 | ***0.64*** | ***1.18*** | -3.08 | -3.12 | ***3.23*** | ***0.97*** | -0.37 | -2.58 |
| | VOL | ***0.61*** | -4.88 | -3.38 | -3.81 | -2.10 | -13.67 | -1.53 | **0.65** | -4.00 | -13.43 |
| | OVN | -0.21 | -0.13 | -2.20 | -2.11 | ***0.01*** | ***0.17*** | -3.49 | -2.59 | -3.88 | -2.83 |
| WMT | RPV | -16.84 | -16.25 | **0.65** | **0.88** | ***4.93*** | -0.30 | -3.85 | -5.53 | ***0.89*** | -5.83 |
| | VOL | -8.72 | -4.93 | ***4.44*** | ***4.97*** | **0.41** | ***0.49*** | -6.46 | -8.47 | -6.08 | -8.02 |
| | OVN | -3.46 | -3.32 | -0.73 | -0.78 | **0.02** | **0.03** | ***0.68*** | ***0.72*** | **0.69** | ***0.75*** |

The reported figures are the average annualized percentage fees (%) that an investor with quadratic utility and constant relative risk aversion of $\gamma=\{1,10\}$ would be willing to pay to switch from using only daily returns (baseline GARCH forecasts) to using additional information (augmented GARCH forecasts) such as intraday-based realized power variation (RPV), trading volume (VOL) or the squared overnight return (OVN) as lagged regressor $\nu_{t-1}$ in Eq. (1b). For each trading strategy-stock combination, bold denotes positive switching fees and italics the largest fees.

**Table 6. Risk-adjusted and utility-based performance evaluation: S&P500 index trading.**

| | Trading strategy | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Directional | | | | Directional SMA-DCMA | | | | Top20 | | | | Bottom20 | | | | Long-short | | | |
| $v_{t-1}$ | $\Delta SoR$ | $\Delta\alpha$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Delta SoR$ | $\Delta\alpha$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Delta SoR$ | $\Delta\alpha$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Delta SoR$ | $\Delta\alpha$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ | $\Delta SoR$ | $\Delta\alpha$ | $\Phi_{\gamma=1}$ | $\Phi_{\gamma=10}$ |
| **Panel A: Before transaction costs** | | | | | | | | | | | | | | | | | | | | |
| RPV | **0.26** | **2.87** | **2.54** | **0.11** | -0.14 | -0.79 | -0.74 | -0.62 | -0.02 | -0.20 | -0.22 | -0.34 | -0.25 | -0.68 | -0.68 | -1.25 | -0.06 | -0.88 | -0.91 | -1.59 |
| VOL | ***0.45*** | ***5.31*** | ***5.74*** | ***5.97*** | ***0.67*** | ***5.71*** | ***4.97*** | ***2.34*** | ***0.59*** | ***7.39*** | ***7.15*** | ***5.91*** | N/A | ***1.60*** | ***1.60*** | ***1.36*** | ***0.73*** | ***9.09*** | ***8.85*** | ***7.35*** |
| OVN | **0.38** | **4.06** | **4.44** | **3.05** | -0.51 | -2.83 | -2.74 | -3.10 | -0.05 | -0.97 | -1.07 | -3.58 | N/A | 0.00 | 0.00 | 0.00 | -0.05 | -0.97 | -1.07 | -3.58 |
| **Panel B: Net of transaction costs** | | | | | | | | | | | | | | | | | | | | |
| RPV | **0.19** | **1.53** | **1.20** | -1.20 | -0.26 | -1.44 | -1.43 | -1.29 | -0.01 | -0.10 | -0.12 | -0.24 | -0.45 | -1.18 | -1.18 | -1.75 | -0.09 | -1.25 | -1.31 | -1.98 |
| VOL | ***0.46*** | ***5.69*** | **6.49** | ***6.72*** | ***1.00*** | ***6.95*** | ***6.48*** | ***3.95*** | ***0.55*** | ***6.83*** | ***6.71*** | ***5.47*** | ***23.25*** | 1.49 | ***1.49*** | ***1.27*** | ***0.68*** | ***8.44*** | ***8.36*** | ***6.87*** |
| OVN | **0.39** | **3.94** | **4.55** | **3.16** | -0.33 | -2.38 | -2.40 | -2.79 | 0.00 | -0.46 | -0.57 | -3.11 | N/A | 0.00 | 0.00 | 0.00 | 0.00 | -0.46 | -0.57 | -3.11 |

The table reports for each augmented-GARCH model the incremental annualized Sortino ($\Delta SoR$) and Leland's alpha ($\Delta\alpha\%$) vis-a-vis the standard GARCH model. The augmentation variable, $v_{t-1}$ in Eq. (1b), is realized power variation (RPV), trading volume (VOL) or the squared overnight return (OVN). Bold indicates that the augmented-GARCH forecasts entail a positive gain relative to the baseline GARCH forecasts. For each strategy-stock pair, italics font denotes the forecasting model that provides the largest incremental gain. N/A indicates that *SoR* cannot be computed because there are very few trades and the investor holds instead the risk free rate over most of the out-of-sample period so all the returns are positive.