

# News - good or bad - and its impact on volatility predictions over multiple horizons\*

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## Abstract

We examine whether the sign and magnitude of intra-daily returns have impact on expected volatility the next day or over longer future horizons. We first let the data 'speak', namely with minimal interference we capture the mapping between intra-daily returns and future volatility. We revisit the concept of news impact curves introduced by Engle and Ng (1993). Overall, we find that moderately good (intra-daily) news reduces volatility (the next day), while both very good news (unusual high intra-daily positive returns) and bad news (negative returns) increase volatility, with the latter having a more severe impact. The asymmetries disappear over longer horizons. We also introduce a new class of parametric models applicable to a mixture of high and low frequency data which feature asymmetries. The new class of models also has close ties to ARCH-type models. Models featuring asymmetries dominate in terms of out-of-sample forecasting performance, especially during the 2007-2008 financial crisis.

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# 1 Introduction

After more than two decades of research on volatility forecasting it is still the case that, while most researchers agree that volatility is predictable, there is considerable disagreement on how volatility predictability should be modeled. Persistence of volatility is a well established stylized fact and remains the salient feature of many models. Other empirical regularities, however, are not so commonly embraced in volatility forecasting. One prominent example is the observation that equity returns and volatility are negatively correlated. The phenomenon can be attributed either to a leverage effect, or a volatility feedback effect. Both effects entail different causality patterns: the leverage effect has return shocks affecting conditional volatility, whereas the feedback effect emphasizes the impact of volatility on time-varying equity risk premia. Various papers have documented the empirical evidence and/or disentangled the causal effects, see e.g. Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), Nelson (1991), Schwert (1990), Campbell and Hentschel (1992), Engle and Ng (1993), Bekaert and Wu (2000), and Bollerslev, Litvinova, and Tauchen (2006) among others. The volatility models that exploit this phenomenon are typically called asymmetric, since 'good' and 'bad' news have a different impact, and to capture the asymmetry Engle and Ng (1993) introduced the notion of a *news impact curve*, both as an object of economic interest and a diagnostic tool for volatility modeling.<sup>1</sup>

In recent years, the literature on volatility modeling has put great emphasis on the wide availability of intra-daily financial returns data. Contrary to a decade ago, data of every stock market transaction is now readily available and it enables one to measure so called realized volatility - an ex post sample realization of the increments in quadratic variation of an underlying price process. Therefore, *measurement* rather than *modeling*, has been the prime focus in the past decade. Measurement, as it turns out, is not easy, as transactions may be affected by microstructure noise and quadratic variation increments may contain a jump component which one might want to extract. The simple measures of realized

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<sup>1</sup> It is important to note that our paper deals with asymmetries of stock market indices - namely Dow Jones and S & P 500 - rather than individual firms where the issue is less relevant. The empirical stylized fact of negative correlation between returns and conditional volatility is also associated with negative skewness. The topic of skewness for market indices on the one hand and for individual firms on the other, has received a fair amount of attention in a number of recent papers - although from a option pricing perspective, see e.g. Conrad, Dittmar, and Ghysels (2009) and Zhang, Zhao, and Xing (2009), for individual stocks and for stock market indices, Chang, Christoffersen, Jacobs, and Vainberg (2009) and Conrad, Dittmar, and Ghysels (2009). Asymmetries and skewness estimates for index returns are reliably negative. However, for individual stock returns the asymmetries and skewness estimates are quite heterogeneous in the cross-section.

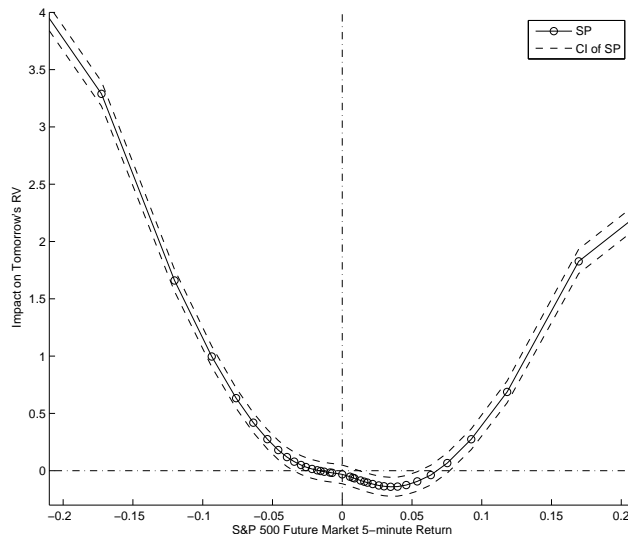
volatilities involve the intra-daily sum of high frequency *squared* returns. More sophisticated measurements that separate jumps or account for microstructure noise, one way or another, are also based on squared returns.

The volatility prediction models that use the new more sophisticated measures of volatility are simple - i.e. usually linear regressions are used involving past realized volatility possibly corrected for jumps or microstructure noise (see Andersen, Bollerslev, and Diebold (2007) and the many references therein). With the focus shifted towards measurement, it is indeed the case that the correlation between returns and volatility has no impact on the in-sample asymptotic analysis that was developed against the backdrop of increasingly available high frequency financial data (see Jacod (1994), Jacod (1996) and Barndorff-Nielsen and Shephard (2007)). The observation that leverage does not affect measurement appears to have given credence to the fact that asymmetries do not matter for forecasting. It is worth recalling that originally, news impact curves were formulated within the context of daily ARCH type models. One may therefore wonder whether it is because daily data was used, that leverage mattered, and that the use of high frequency now has nullified the issue. The paper shows that asymmetries still matter a lot. To show this, we make various contributions to the existing literature.

It is not obvious how one would go about answering the question whether the sign and magnitude of discretely sampled high frequency returns have any impact on future volatility predictions. First, the raw input is a return over a short interval and the prediction period is not the next short interval, but rather some arbitrary future period - say the next day, week, etc. The mismatch of observation frequency and prediction horizon brings about issues that cannot be handled easily by simple linear models or ARCH-type models. Then there is also the pervasive intra-daily seasonality that prevents one from putting each high frequency interval on equal footing.

We first let the data 'speak', namely with minimal interference we capture the mapping between returns over short horizons and future volatility over longer horizons. To cut straight to the main point, consider an illustrative example of our findings. We take five minute returns on the S&P 500 futures market as the primitive input, and the next day's realized volatility as the future outcome of interest - hence we are thinking along the lines of Engle and Ng (1993) but without a daily volatility model. The typical picture for one day ahead (ignoring the intra-day effects) that emerges from our analysis appears below. The X-axis measures 5-minute returns in the S&P 500 futures market - scaled to annual units. The

Y-axis is their expected impact on tomorrow’s volatility (with confidence bands) - scaled by average daily realized volatility. The pattern that emerges is interesting. Good news *reduces* tomorrow’s expected volatility, i.e. the expected impact dips below zero.<sup>2</sup> In contrast, *very good news* tends to increase volatility, as does *bad* news. This asymmetric pattern has been recognized in the past, notably by Engle and Ng (1993). However, here we can carry this further across different horizons using high frequency intra-daily data.



The above plot also reveals that we are essentially dealing with two issues: mis-specification and aggregation. Mis-specification, because measures of quadratic variation are based on squared returns, while the above plot tells us that response functions are not symmetric. Aggregation, because we will build models using high frequency data directly, while all existing models square intra-daily returns and add them up to daily realized variance.

Technically speaking, we start with a semi-parametric MIDAS regressions, inspired by recent work on MIDAS regressions, in particular in the context of volatility as in Ghysels, Santa-Clara, and Valkanov (2006) and Forsberg and Ghysels (2006). The approach adopted in the paper generalizes the original MIDAS regression setup in two important ways. First, it allows for a nonparametric specification of the news impact curve, as depicted in the illustrative

<sup>2</sup> For the purpose of clarification we should note that this negative impact pertains to one single five minute interval and the total impact over one or several days is a weighted sum of every five minute’s impact. This brings about non-negativity issues regarding the prediction of future volatility - which will be discussed in the paper.

plot, and second, a multiplicative scheme is introduced designed to accommodate intra-daily trading patterns. More importantly, we introduce various new parametric models applicable to intra-daily returns, that are inspired by the asymmetric (daily) GARCH models. These simple parametric models do out-perform standard models based on daily realized measures. For example, when we study two specific out-of-sample forecast exercises, one during the relatively calm 2005-2006 low volatility period and the other during the 2007-2008 crisis, we come to the following conclusions. For the calm low volatility period, the standard symmetric models and the new models featuring asymmetries fare equally well. During the financial crisis, however, the out-of-sample forecasting gains of asymmetric models in comparison to the standard ones range from roughly 5 % to as high as 20 % in terms of mean squared error - depending on the series and forecasting horizon. Formal statistical tests show these gains are statistically significant.

The paper is organized as follows. In sections 2 and 3 we introduce various new models, some involving daily realized measures, some based directly on intra-daily returns in the context of news impact curves and volatility prediction. Empirical results are reported in section 4. Section 5 concludes the paper.

## 2 Volatility Measurement and Model Specifications

In a first subsection we briefly review recent advances in volatility measurement, whereas the second subsection covers the models of recent vintage that use high frequency data volatility measures. The prime purpose of this section is to provide a succinct overview of existing models. At the end of the section, however, we introduce a new model using daily realized volatilities that captures asymmetries.

### 2.1 Measuring Volatility

The foundation of realized volatility modeling is the theory of continuous time semi-martingale stochastic processes, more specifically stochastic volatility continuous time jump-diffusions. The recent vintage of volatility models are based on so called Realized Measures of which Realized Variance (RV) - measured by the sum of squared intra-daily returns - is the most prominent example. More specifically, we consider the log asset price difference

(return)  $r_{t,i\Delta}$  over some short time interval  $i$  of length  $\Delta$  on day  $t$ . We have  $i = 1, \dots, \Delta^{-1}$  of intervals on day  $t$ . The high frequency intra-daily returns are used to compute Realized Variance, namely:

$$RV_{t,t+k}(\Delta^{-1}) \equiv \sum_{j=t}^{t+k} \sum_{i=1}^{\Delta^{-1}} r_{j,i\Delta}^2 \quad (2.1)$$

for  $k = 1, \dots$ . We will typically drop  $\Delta$  as an argument of  $RV$  to simplify notation.<sup>3</sup> Realized Variance may include jumps and the separation between the continuous path part of integrated volatility (the population counterpart of  $RV$ ) and the jump component is sometimes taken into account when formulating a prediction model for volatility. The non-jump component is estimated via another Realized Measure, the so called bi-power variation, or:

$$BPV_{t,t+k}(\Delta^{-1}) \equiv \sum_{j=t}^{t+k} \sum_{i=2}^{\Delta^{-1}} |r_{j,i\Delta}| |r_{j,(i-1)\Delta}| \quad (2.2)$$

Without elaborating on the specifics of tests for jumps it suffices to say that we follow Andersen, Bollerslev, and Diebold (2007) who use Hausman-type tests involving  $RV$  and  $BPV$ . It is important to note, however, that such tests are purely symmetric, namely they involve either squared or absolute returns - and therefore do not discriminate between positive and negative returns.

In the context of stochastic volatility continuous time jump-diffusions, asymmetries are modeled via the correlation between the Brownian motion that drive returns and the one that drives volatility dynamics (assuming a single factor structure). If we think of asymptotics in terms of sampling at ever finer intra-daily intervals (i.e.  $\Delta \rightarrow 0$ ), it has been shown that such leverage does not affect the measurement of realized volatility (see inter alia Jacod and Protter (1998) and Barndorff-Nielsen and Shephard (2007)).<sup>4</sup>

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<sup>3</sup> Microstructure noise may mask the true price variation. Various corrected measures of  $RV$  have been suggested. See for example Aït-Sahalia, Mykland, and Zhang (2005), Bandi and Russell (2006), Bandi and Russell (2005), Barndorff-Nielsen, Hansen, Lunde, and Shephard (2006) and Hansen and Lunde (2006). In our empirical work we consider series for which it is reasonable to assume that they are sampled without microstructure noise - more on this in Section 4. We therefore do not elaborate on the subject in the development of our models.

<sup>4</sup> The standard no-arbitrage semimartingale setting subject only to weak technical regularity conditions suffices to establish this result. Recent work by Barndorff-Nielsen, Kinnebrock, and Shephard (2008) - discussed later - provides a discussion of the technical conditions.

## 2.2 Forecasting Volatility

We are interested in predicting tomorrow's volatility, and consider the regression model:

$$RV_{t,t+1} = \psi_0 + \sum_{j=0}^{\tau} \psi_j(\theta) RV_{t-j-1,t-j} + \varepsilon_{t,t+1} \quad (2.3)$$

Within the class of linear models the specification in (2.3) is quite generic, as it covers models considered by Andersen, Bollerslev, and Diebold (2007), Ghysels, Santa-Clara, and Valkanov (2006), Forsberg and Ghysels (2006), Corsi (2009), among many others. The various approaches differ with respect to the parametrization of  $\psi_j(\theta)$ . For example, the so called HAR-RV (where HAR stands for Heterogeneous Autoregressive) of Andersen, Bollerslev, and Diebold (2007), is:

$$RV_{t,t+k} = \psi_0 + \psi_D RV_{t-1,t} + \psi_W RV_{t-5,t} + \psi_M RV_{t-22,t} + \varepsilon_{t,t+k} \quad (2.4)$$

which predicts future volatility via a linear regression on past daily, weekly and monthly  $RV$ .<sup>5</sup> The fact that  $RV$  may contain jumps has led to an alternative specification, called HAR-RV-J, as it separates the jump component:

$$RV_{t,t+k} = \psi_0 + \psi_D BPV_{t-1,t} + \psi_W BPV_{t-5,t} + \psi_M BPV_{t-22,t} + \psi_J J_t + \varepsilon_{t,t+k} \quad (2.5)$$

where  $J_t$  equals one when day  $t$  has a jump and is zero otherwise.

The HAR-RV and HAR-RV-J models share one common feature, namely symmetry. The sign of intra-daily returns does not matter, since both  $RV$  is symmetric and tests for jumps are based on even power transformations of intra-daily returns as well. There are some notable exceptions in the recent literature that have tried to accommodate asymmetries, including Barndorff-Nielsen, Kinnebrock, and Shephard (2008) and Engle and Gallo (2006). Both consider some form of 'signed' daily variances, i.e. variance measures multiplied by a sign indicator function. In particular Barndorff-Nielsen, Kinnebrock, and Shephard (2008)

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<sup>5</sup> It may not be so directly apparent that equation (2.3) nests (2.4). As noted by Andersen, Bollerslev, and Diebold (2007) (footnote 16) equation (2.4) is in a sense a so called MIDAS regression with 'step functions' (in the terminology of Ghysels, Sinko, and Valkanov (2006a)). See also the discussion in Corsi (2009) - page 181 - on this topic.

introduce the notion of semi-variance:

$$SemiV_{t+k,t}^+ \equiv \sum_{j=1}^k \sum_{i=1}^{\Delta^{-1}} r_{j,i\Delta}^2 \mathbf{1}_{r_{j,i\Delta} > 0} \quad (2.6)$$

and  $SemiV_{t+k,t}^- \equiv RV_{t+k,t} - SemiV_{t+k,t}^+$ .<sup>6</sup>

## 2.3 Benchmark Models

The empirical analysis will involve formal statistical tests to assess whether the new models we are about to introduce significantly outperform the state-of-the-art models (2.4) and (2.5) which will be chosen as benchmarks. To raise the bar in terms of benchmark even higher, we also introduce a new model that includes asymmetries in terms of semi-variances. We call this new model HAR-S-RV-J, which is specified as:

$$\begin{aligned} RV_{t,t+k} = & \psi_0 + \psi_D^+ SemiV_{t-1,t}^+ + \psi_D^- SemiV_{t-1,t}^- \\ & + \psi_W^+ SemiV_{t-5,t}^+ + \psi_W^- SemiV_{t-5,t}^- \\ & + \psi_M^+ SemiV_{t-22,t}^+ + \psi_M^- SemiV_{t-22,t}^- + \psi_J J_t + \varepsilon_t \end{aligned} \quad (2.7)$$

so that past daily, weekly and monthly  $RV$  are split into semi-variances, and hence are allowed to have an asymmetric response. As noted before, this model is new to the literature, yet it is a natural extension of existing specifications and it is a natural benchmark to compare with the models discussed next. It has one drawback, namely ideally we would like to split  $BPV$  instead of  $RV$  into semi-BPV measures so that the HAR-S-RV-J model nests the HAR-RV-J one. Unfortunately, defining  $BPV$  as a semi-bi-power realized measure is not straightforward. We keep the jump component, nonetheless, as the prior literature has emphasized the importance of jumps.<sup>7</sup> In fact, this shows the limitations of dealing with jumps and asymmetries through aggregate measures. Our approach will circumvent these limitations.

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<sup>6</sup>To facilitate the presentation, we use the following indicator process:  $\mathbf{1}_A$  which is one when  $A$  is true, and equals zero otherwise.

<sup>7</sup>Barndorff-Nielsen, Kinnebrock, and Shephard (2008) discuss how to separate the jump component in positive and negative jumps - something we do not pursue here.

### 3 A new class of high frequency data volatility prediction models

Consider the prediction of tomorrow's volatility. The models considered in the previous section used past realized volatility, bi-power, jumps and semi-variances as information. The models in this section will formulate a prediction for tomorrow's volatility in terms of all the high frequency returns of today and previous days as information. Hence, we do *not* aggregate high frequency returns to daily RV measures. Instead, we use the intra-daily returns directly as regressors, for the purpose of forecasting future daily, weekly or monthly volatility. Note two important issues, namely (1) we gain information since we do not aggregate intra-daily returns and (2) we do not impose the quadratic variation transformation - that is sums of squared intra-daily returns - but instead let the regression fit decide what impact news - a five minute return - has on future volatility.

The new class of models relates to several recent contributions pertaining to MIDAS-type regressions, i.e. involving so called mixed data sampling. Examples of MIDAS regressions for the purpose of volatility forecasting include Ghysels, Santa-Clara, and Valkanov (2006); Forsberg and Ghysels (2006), Becker, Clements, and White (2007), León, Nave, and Rubio (2007), among others. The approach adopted in the paper generalizes the original MIDAS regression setup in two important ways. First, we introduce semi-parametric MIDAS regressions that will allow us to estimate non-parametrically a news impact curve introduced in the context of ARCH-type models by Engle and Ng (1993). The regressions are semi-parametric because they contain a parametric temporal dependence structure and a non-parametric news impact. Second, the parametric specification of the temporal dependence allows explicitly for intra-daily seasonal patterns, something the prior literature on MIDAS regressions so far has ignored.

To predict future volatility with past high-frequency returns, we propose the following regression model (again for simplicity restricting ourselves to a single day forecast):

$$RV_{t,t+1} = \psi_0 + \sum_{j=1}^{\tau} \sum_{i=1}^{\Delta-1} \psi_{ij}(\theta) NIC(r_{t-j,i\Delta}) + \varepsilon_{t,t+1} \quad (3.1)$$

where  $\psi_{ij}(\theta)$  is a polynomial lag structure parameterized by  $\theta$  and  $NIC(\cdot)$  is the news impact curve. The regression in (3.1) tells us that each intra-daily return  $r_{t-j,i\Delta}$  has an

impact on future volatility measured by  $NIC(r_{t-j,i\Delta})$  and fading away through time with weights characterized by  $\psi_{ij}(\theta)$ . We will refer the above regression as the SP model, since it is a semi-parametric setup. It is worth noting at this point that equation (3.1) nests the models of the previous section - in particular the generic equation (2.3) - when we set  $\psi_{ij} \equiv \psi_i \forall j = 1, \dots, \Delta^{-1}$ , and  $NIC(r) \equiv r^2$ . This nesting emphasizes the role played by both the news impact curve  $NIC$  and the lag polynomial  $\psi_{ij}$  to which we turn our attention in the remainder of the section.

We elaborate first on the news impact curve and then discuss the polynomial lag specification. A subsection is devoted to each topic. Before we do, we need to make an observation about comparisons with the models of the previous section. Indeed, some models were based on the separation of increments in quadratic variation into a jump and continuous path component. Such decomposition does not feature in the above regressions as they are rooted in a discrete time modeling approach similar to ARCH. Obviously, extreme high frequency returns - perhaps due to jumps - and their impact will be measured by the behavior of the  $NIC$ . Positive and negative jumps may therefore have an asymmetric impact, due to the asymmetry of the curve. This might be viewed as an advantage considering the fact that the discussion in the previous section revealed it is not straightforward to decompose  $RV$  into semi-variances and at the same time account for jumps.

The section is organized as follows. Subsection 3.1 covers news impact curves. Next we discuss the specification of the polynomials. Finally, we digress in subsection 3.3 on estimation issues.

### 3.1 News Impact Curves - Parametric and Non-Parametric

Which shape does an intra-daily news impact curve have? While there is considerable amount of evidence using daily data, we are - as far as intra-daily returns are concerned - in uncharted territory. It is therefore natural to start with a minimal amount of a priori restrictions - the reason why we start with a semi-parametric approach, which involves non-parametric estimation of  $NIC$  and parametric estimation of  $\psi_{ij}(\theta)$ . As is typically the case, there is a serious drawback when we simply let the 'data speak'. The estimation procedure is cumbersome, and convergence rates are slow - which means lots of data is required to estimate a  $NIC$ . In the present context, it is however, warranted as a starting point. The non-parametric estimates will provide useful guidance for the second approach, which is

purely parametric and relies heavily on the existing ARCH literature. It is the purpose of this subsection to discuss both the non-parametric approach and parametric specifications of intra-daily news impact curves.

The semi-parametric approach is much inspired by the recent work of Linton and Mammen (2005) who propose the semi-parametric ARCH( $\infty$ ) model. We extend it here to the regression appearing in (3.1) involving a mixed data sampling scheme, which as it turns out, changes the nature of the asymptotic distribution (as discussed in the final subsection).<sup>8</sup> The main drawback of estimating  $NIC$  non-parametrically is computational complexity. The parametric models, in contrast, can be estimated in a fraction of time compared to the semi-parametric specifications.

There are several other reasons for looking at parametric models. First, the models we will consider relate to ARCH-type models and hence bridge a new and old literature. Second, formal testing in the context of semi-parametric models is quite challenging while this is not in the case for parametric models. Chen, Ghysels, and Renault (2009) derive asymptotic confidence bands for estimated news impact curves  $\widehat{NIC}$  - with details also appearing in Appendix A. It is not straightforward, however, to test the hypothesis of asymmetry in the context of non-parametric estimation. We therefore resort to parametric models to test asymmetry of news impact curves.

The parametric models we introduce are both old and new. Not surprisingly, the parametric specifications are inspired by news impact curves adopted in the ARCH literature, namely:

- $NIC(r) = br^2$ , to which we attach the acronym SYMM. The SYMM model can be regarded as a MIDAS extension of ARCH to the case of high-frequency data. Obviously, the SYMM model cannot capture any asymmetries that appear in the data. Note that equation (3.1) with a quadratic  $NIC$  is in one very important way different from the  $RV$ -based regression (2.3). The latter aggregates on a daily basis all intra-daily squared returns whereas SYMM predicts future volatility without the aggregation of intra-daily squared returns - potentially attributing different weights throughout the trading day (the specification of the polynomials will be discussed in the next subsection).
- Inspired by the GJR model proposed by Glosten, Jagannathan, and Runkle (1993), we

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<sup>8</sup> We assume that  $\tau$  is finite - yet we could easily assume it to be infinite. We also assume that  $\Delta$  is finite. This is a less innocent assumption particularly with respect to the current literature on measurement of realized volatility.

consider the ASYMGJR model with  $NIC(r) = br^2 + (cr^2)\mathbf{1}_{r < 0}$ .

- Another possible way to allow for asymmetric effects is via a location shift, as in the Asymmetric GARCH model in Engle (1990), yielding the ASYMLS model with  $NIC(r) = (b(r - c)^2)$ .<sup>9</sup>

### 3.2 News Impact Throughout the Day

We turn our attention now to the specification of the polynomial lag structure  $\psi_{ij}(\theta)$  appearing in equation (3.1). It was noted that the SYMM model, i.e. equation (3.1) with a quadratic  $NIC$  differs from the  $RV$ -based regression (2.3) in an important way, namely that the former does not aggregate throughout the day the intra-daily returns. Inspired by this temporal aggregation argument we design the parametric specification of the polynomial lag structure. Suppose for the moment that the  $NIC$  is quadratic. How could we possibly nest models based on  $RV$ ? We can achieve this if we adopt a multiplicative specification for  $\psi_{ij}(\theta) \equiv \psi_j^D(\theta) \times \psi_i^{ID}(\theta)$ , with the parameter  $\theta$  containing subvectors that determine the two polynomials separately. The polynomial  $\psi_j^D(\theta)$  is a daily weighting scheme, similar to  $\psi_i(\theta)$  in the regression model appearing in (2.3). The polynomial  $\psi_i^{ID}(\theta)$  relates to the intra-daily pattern. We noted before that with equal intra-daily weights we de facto have the  $RV$  measure when  $NIC$  is quadratic - as is the case in the aforementioned SYMM model. We adopt the following specification for the polynomials:

$$\psi_j^D(\theta)\psi_i^{ID}(\theta) = \text{Beta}(j, \tau, \theta_1, \theta_2) \times \text{Beta}(i, \Delta^{-1}, \theta_3, \theta_4) \quad (3.2)$$

where the (single) Beta polynomial specification has been used in prior work, notably in Ghysels, Santa-Clara, and Valkanov (2002).<sup>10</sup> It should first be noted that we impose the restriction that the intra-daily patterns wash out across the entire day, i.e.  $\sum_i \text{Beta}(i, \Delta^{-1}, \theta_3, \theta_4) = 1$ . We also impose, without loss of generality, a similar restriction on the daily polynomial, which allows us to identify a slope coefficient in the regressions.

The multiplicative specification has several advantages. First, as noted before, a so called

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<sup>9</sup>We also considered two models which combine the GRJ model and Asymmetric GARCH model: ASYMC1 model,  $NIC(r) = (b1_{r-d < 0}(r - d)^2 + c1_{r-d \geq 0}(r - d)^2)$ ; and ASYMC2 model,  $NIC(r) = (b1_{r < 0}(r - d - e)^2 + c1_{r \geq 0}(r - d)^2)$ . Due to space limitations we do not report the results as they are roughly similar to the ASYMGJR specification.

<sup>10</sup>More specifically:  $\text{Beta}(k, K, \alpha, \beta) = (k/(K + 1))^{\alpha-1}(1 - k/(K + 1))^{\beta-1}\Gamma(\alpha + \beta)/\Gamma(\alpha)/\Gamma(\beta)$ . See also Ghysels, Sinko, and Valkanov (2006b) for further discussion.

flat aggregation scheme, i.e. all intra-daily weights are equal, yields de facto a daily model with  $RV$  when the news impact curve is quadratic. Or more formally, when  $\theta_3 = \theta_4 = 1$ , and  $NIC(r) = r^2$  we recover  $RV$ -based regression appearing in equation (2.3). Second, by estimating  $Beta(i, \Delta^{-1}, \theta_3, \theta_4)$  we let the data decide on the proper aggregation scheme.<sup>11</sup> Obviously, the intra-daily part of the polynomial will pick up how news fades away throughout the day and this - in part - depends on the well known intra-daily seasonal pattern.<sup>12</sup>

The intra-daily seasonal pattern may not be fully captured by the  $Beta(i, \Delta^{-1}, \theta_3, \theta_4)$  polynomial. It appears to work very well empirically, however, and its virtue is that it requires only the estimation of two parameters. Other more complex specifications could be considered - a topic we leave for future research.

To conclude, it should be noted that Ghysels, Santa-Clara, and Valkanov (2006) applied a single polynomial lag structure that ignored intra-daily seasonality, despite it being pervasive, which is why their results left the impression that the information in the intra-daily information was not useful.

### 3.3 Estimation Issues

The estimation of the parametric models is straightforward, as it involves either OLS (for HAR-RV, HAR-RV-J and HAR-S-RV-J) or nonlinear least squares (for models that use intra-daily returns, namely SYMM, ASYMGJR, and ASYMLS). Nonlinear least squares is required in the latter cases, as the polynomials appearing in equation (3.2) are nonlinear functions of the parameter vector  $\theta$ . All the regressions are based on non-overlapping samples of  $RV$ , hence the sample sizes for the daily, weekly and monthly horizons are not the same. The advantage, however, is that we do not have to deal with autocorrelation of the residuals induced by overlapping forecast horizons. In contrast, heteroskedasticity may still be a

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<sup>11</sup>This is a generic issue pertaining to MIDAS regressions and temporal aggregation, see Andreou, Ghysels, and Kourtellis (2009) and Ghysels (2009) for further discussion.

<sup>12</sup>Wood, McNish, and Ord (1985), one of the earliest studies employing intra-daily data, documents the well known U-shaped pattern. Much has been written on the topic of seasonality in economic time series (see e.g. Ghysels and Osborn (2001)). Broadly speaking there are two approaches: (1) seasonally adjust series and construct non-seasonal models subsequently, or (2) build seasonal features of the data into the model specification. Intra-daily seasonality has been tackled similarly. See e.g. Andersen and Bollerslev (1997), Andersen and Bollerslev (1998), Bollen and Inder (2002), Dacorogna, Gençay, Müller, Olsen, and Pictet (2001), Martens, Chang, and Taylor (2002), among others.

concern. A simple test which consists of fitting an AR(1) model to the squared residuals of the regressions shows that heteroskedasticity is present in most regressions with daily and weekly horizons and that heteroskedasticity is not present at the monthly forecast horizon. For the daily and weekly horizons it appears that roughly all models are affected equally. Hence, there is room for improvement roughly equally across all the models. For simplicity, we proceed with the estimation results, without correcting for heteroskedasticity in terms of estimation, yet we do correct the standard errors via HAC estimators.

The estimation of the semi-parametric MIDAS regression model warrants some discussion. The asymptotic analysis of semi-parametric MIDAS regressions is summarized in Appendix A. The asymptotic distribution of the estimation procedure has a parametric and non-parametric part. The latter is kernel-based and involves solving a so called inverse problem. Chen, Ghysels, and Renault (2009) show that the mixed data sampling scheme in semi-parametric MIDAS regressions only adds an extra term to the asymptotic variance, i.e. when  $\Delta = 1$ , the asymptotic distribution collapses to the case covered in Linton and Mammen (2005). As mentioned above, the non-parametric estimation of the *NIC* function is kernel-based and involves solving a so called inverse problem. Loosely speaking a key equation to solve (see equation (A.6) in Appendix A) can be written as:

$$NIC(x) = NIC^*(x) + \int H(x, y)NIC(y)f(y)dy$$

where  $f$  is a density function for 5 minute returns,  $H$  is based on densities involving five minute returns and we skip the details of the intercept function  $NIC^*(x)$ . The non-parametric estimation of *NIC* requires solving the above integral equation and this is done via a discretization of the integral equation. Namely, one has to select a number of discrete points for  $x$  and  $y$  in the above equation becomes a linear system of equation where one can invert the  $H$  as a matrix evaluated across all pairs of  $x$  and  $y$ .

We learned from experimentation that there appear to be two critical choices that affect the estimation outcome. They are (1) the bandwidth selection for the kernels, and (2) the number of grid points. Regarding the bandwidth, we followed the asymptotically optimal bandwidth selection procedure described in Section 6.1 of Linton and Mammen (2005). In theory, one should choose as many as possible grid choices to appraise robustness; however, in practice, the estimation time is roughly equal to  $\Delta T \times \tau/\Delta \times n_g^2$  where  $\Delta T$  is the sample size,  $\tau/\Delta$  is the number of lags and  $n_g$  is the number of grid points and therefore

prohibitively costly with dense grids. In the software used by Linton and Mammen (2005) and kindly supplied to us, the grid number choice is 100 or 200; but they are dealing with low-frequency, daily that is, data. We choose a grid equal to 41, which means the quantile interval is 2.5%, with an estimation time of roughly 20 hours for PC with P4 2.4G CPU and 1GB of memory. We also tried a grid of 80, which does not significantly improve (or make worse) our results.

The shape of the news impact curve also raises the issue of positivity constraints. It is important to note that each and every day has many five-minute intervals, and for some  $NIC(.)$  is positive, whereas for others the functional yields a negative value. As far as positivity is concerned, what matters is the final model prediction which compounds all the high frequency intervals - so the fact that the function dips below zero over a single interval is not of major concern, as long as the sum of all weighted functionals of five minute returns remains positive. In none of our empirical examples did it ever happen that predictions yielded negative volatilities. The non-negativity constraint that also appears in the Linton and Mammen code supplied to us was never binding in-sample.

## 4 Empirical Results

We analyze four data sets which consist of five-minute intra-daily returns of respectively Dow Jones and S&P 500 cash and futures markets. The data are described in the top panel of Table 1. The samples of Dow Jones cash and futures markets start in 1993 and 1997 respectively and hence do not include the 1987 crash, while the samples of S&P 500 cash and futures markets start in 1985 and 1982 and therefore include the 1987 crash (for models fitted with S&P 500 data). All samples end December 31, 2008 and therefore include the most recent financial crisis. The 1987 crash, however, will appear in the estimation samples - whereas the 2007-2008 financial crisis will be exploited for the purpose of out-of-sample forecasting. All the models are based on five-minute data, which brings us to the question of microstructure noise. In the case of S&P 500 futures our data sample includes that of Bollerslev, Litvinova, and Tauchen (2006), who document that transactions in the futures market occur on average roughly every 9 seconds. This means that, at least for the futures data, one may safely assume that microstructure effects are negligible, an assumption also

underlying the analysis in Bollerslev, Litvinova, and Tauchen (2006).<sup>13</sup>

We look at different prediction horizons for future volatility. This will allow us to appraise how asymmetries play out at different horizons. So far we wrote equations predicting  $RV$  only one day ahead, and we noted that longer horizons are straightforward extensions. In the empirical work we consider three horizons (1) one day, (2) one week and (3) one month. We start with full-sample estimates, and then we consider various sub-samples. A major concern is that of in-sample over-fitting. We guard against this in two ways. First we examine out-of-sample prediction performance for some fixed samples. Second, we also examine rolling sample estimates with repeated out-of-sample predictions. The latter will allow us to test whether forecasting gains from models featuring asymmetries are statistically significant.

In a first subsection we examine estimated news impact curves. The second subsection is devoted to the out-of-sample prediction performance for some fixed samples, notably pertaining to the financial crisis of 2007-2008. The final subsection appraises the statistical significance of the out-of-sample forecasting performance.

## 4.1 Is News Impact Asymmetric?

We start with the simple question: is there evidence that news has an asymmetric impact when we examine intra-daily data? To answer this question we start with examining the full-sample estimation results of the various models featuring asymmetries introduced in the previous section. This means we look both at the fully parametric specifications, either involving aggregated semi-variances or intra-daily data, and the semi-parametric ones also involving high frequency returns.

Recall that the parametric models have the advantage that we can test the significance of asymmetries via restrictions on the parameters instead of eye-balling curves. We start with the regression model appearing in (2.7) involving semi-variances. This first model, called HAR-S-RV-J and new to the literature, involves past daily, weekly and monthly  $RV$  in the original HAR-RV-J model split into semi-variances. The results appear in Table 2. The

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<sup>13</sup> Microstructure noise distorts the average realized volatility. Consequently, a plot of average realized volatility against the intra-daily sampling frequency may help reveal the severity of microstructure bias as the sampling frequency increases. This is the idea behind the signature plots, suggested by Andersen, Bollerslev, Diebold, and Labys (2000). We computed such plots and they indicate that 5 minutes appears to be a reasonable sampling frequency for all of our series. Signature plots are omitted but available upon request.

top panel reports tests of the single restriction that either the daily, weekly, or monthly semi-variances have equal coefficients. The final column contains a joint test of the null with all three restrictions. The asymptotic variances to compute the tests use HAC standard errors with lag lengths that match the inference recommendations of Andersen, Bollerslev, and Diebold (2007). Entries in Panel A are p-values, since joint and single restriction tests feature different asymptotic distributions. Finally, all the results in the table pertain to full sample estimates. The daily lag coefficients do not seem to feature asymmetries for the four series for predicting future daily volatility, yet it does matter for weekly and monthly forecasts. The weekly lag coefficients only appear to feature asymmetries for predicting future weekly volatility. The monthly semi-variances also matter at all but the daily forecast horizon. The final column reports joint tests that asymmetries are present at all forecast horizons. The evidence suggests that is the case except for the DJ cash series.

In subsequent tests we will use both the HAR-RV-J and HAR-S-RV-J models as benchmarks. The statistical evidence does imply that the HAR-S-RV-J model is indeed a more stringent benchmark as it captures some of the much neglected asymmetries through daily measures. The tests will therefore reveal whether asymmetries at the intra-daily level matter even more.

We turn our attention next to Panel B of Table 2, which pertains to parametric models using intra-daily returns and featuring asymmetries. The panel displays the parameter estimates of the lag polynomials involving parameters  $\theta_1$  through  $\theta_4$ , appearing in equation (3.2). The parameters  $a$ ,  $b$ , and  $c$ , determine the news impact, where  $c$  relates to asymmetries, since for the ASYMGJR model  $NIC(r) = (br^2 + c1_{r<0}r^2)$ , and for the ASYMLS model  $NIC(r) = (b(r - c)^2)$ . To save space, the parameter estimates are reported for one representative series, the S&P 500 Futures contract, at one day and one week forecast horizons (more detailed results are available upon request). The evidence of intra-daily asymmetries is overwhelming, judged by the significance of the parameter estimates of  $c$  in all the models reported.

Unlike the plot appearing in the Introduction, we consider now four news impact curves in Figures 1 and 2 corresponding to two horizons: one-day and one-week ahead. To facilitate the interpretation and display of results, the news impact is scaled by the mean of  $RV$  for each series/horizon. The X-axis measures annualized intra-daily returns.<sup>14</sup> The Y-axis are in terms of fractions of average volatility - namely we scaled the news impact by the mean of the relevant average  $RV$  for each series/horizon. As a consequence, we can compare the news impact curves across series and horizons.

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<sup>14</sup>The annualized returns calculations are obtained through a simple re-scaling.

For the moment it suffices to look at the dotted lines in each of the figures, which represent the news impact curves obtained via the semi-parametric estimation. It is remarkable to note how similar the shapes are for the SP model estimates across the four different series at the daily forecasting horizon and to a lesser extent at the weekly horizon. The asymmetry of the news impact is obvious from the plots. Negative and positive returns have a different impact. The finding that so called *no news is good news* extensively documented in the literature using daily returns implies that the minimum of the news impact curve is at zero. Instead, with intra-daily data we find in Figures 1 and 2 that the intra-daily news impact curves attain their minimum at some mildly positive return, meaning that such returns result in decreased volatility the next day/week (since the impact is negative). As noted in the Introduction, we also recognize the fact that extremely 'good news', the positive returns (it turns out those larger than the 90% quantiles), cause *increased* future volatility. Finally, as noted earlier, 'bad news' has a more acute impact than positive news.

The 95 % asymptotic confidence intervals around the news impact curves tell us that the dip below zero is statistically significant in the case of S&P 500 futures at the daily horizon. At the weekly horizon, the statistically significant negative impact is more marked, except for the S&P 500 cash series. Returns larger than the 10 % annualized return tend to move volatility up by a fraction equal to between half and four to five-fold average volatility both at the daily and weekly horizon. Are these reasonable numbers? One has to keep in mind that the curves measures the impact of a single five minute interval and every day features 78 such intervals, each with their own impact that fades away across time. Hence the units, while comparable across series are not easy to fully comprehend. What matters most about the exercise is the fact that the figures show clearly the presence of asymmetries. Whether the actual news impact is reasonable can only be assessed by looking at forecasting performance - the topic to which we turn our attention in the next subsection.

What about the comparison of the parametric and non-parametric curves? Figure 3 displays the news impact - parametric and non-parametric - for the one week horizon. We also plot the confidence bands for the SP specification that appeared in plot (d) in Figure 2. The parametric approaches are asymmetric: ASYMGJR and ASYMLS. The latter seems to match up reasonably well while the ASYMGJR model appears to be off for both large positive and negative returns. We report this only for a single series - although this pattern is quite representative.

We also report one final intriguing result in Figure 4. It displays the monthly horizon

news impact curves for the four series. One comment is worth making about the confidence intervals. We note that for the DJ series - cash and futures - the bands are much wider. This is due to the smaller sample size, in particular for DJ futures, compared to the S&P series. We also recognize this pattern for the one-day and one-week horizons news impact curves - but the differences are less pronounced as the disparity of sample sizes is less important. The most remarkable observation in Figure 4 is that the curves are symmetric. Hence, over longer horizons asymmetries fade away. We will note later that this indeed matters for forecasting.

Besides the news impact curves, we need to discuss the parametric part of the semi-parametric MIDAS regression, or more specifically the Beta polynomials appearing in equation (3.2). We plot only one of the four examples, namely the S&P 500 Futures example. There are three plots that appear in Figure 5. The first plot displays the product of the daily and intra-daily lags, hence it contains the profile of the coefficients  $\psi_{ij}$ . The second plot displays only the daily coefficients  $\psi_j$  and finally the intradaily coefficients  $\psi_i$  appears in the third plot. The patterns are not surprising, given the abundant evidence documented in the empirical volatility literature. The daily coefficients decrease monotonically and are close to zero after 6 to 8 days. The intra-daily weights display a somewhat asymmetric U-shaped pattern, perhaps best characterized as a smirk. It means that late afternoon returns, carry relatively more weight than morning returns. The product of the two provides a spiky decay pattern compounding the intra-daily and daily response.

The results, so far, clearly indicate that asymmetries matter - whether we look at plots, models using semi-variances, or parametric models that apply directly to intra-daily data. Yet, there appears to be some disagreement with regards to the horizon effect. The evidence from the HAR-S-RV-J model seems to suggest that asymmetries are more important at longer horizons. All other models suggest the opposite - namely at longer horizons asymmetries fade away. In the remainder of this section we analyze how the evidence of asymmetry at various prediction horizons translate into forecasting gains.

## 4.2 Out-of-sample Forecasting Performance

We start with a relatively informal statistical analysis. In the next subsection we turn to more formal out-of-sample forecasting evaluations. More specifically, in the next subsection, we will use rolling sample estimates, hence constantly updating the parameter estimates, and perform repeated forecasts out of sample to construct formal statistical tests. Such

an exercise is computationally demanding and will therefore exclude the semi-parametric specification of the news impact curve - since the estimation of the latter is prohibitively time-consuming. In this subsection, we therefore focus on two specific out-of-sample forecast comparisons. The advantage is that we can include the computationally intensive semi-parametric approach.

We take a look at two interesting samples, the first ends in 2004, the second in 2006. Why are they interesting? All the models are estimated with at the end of the estimation sample two years of data set apart to perform out of sample forecasting (Table 1 lists the sample configurations). Hence, for the sample ending in 2004 we predict out of sample for 2005-2006 - a relatively calm period as far as volatility goes. The second sample ends right before the financial crisis and parameter estimates are then used to predict during the financial crisis.

Since the focus of the paper is on asymmetries, it is worth first of all taking a look at the two out-of-sample periods, namely the 2005-2006 and 2007-2008 samples. In Figure 6 we plot the histograms - throughout the day in different time zones of the trading day - of the 5 minute returns. The histograms reveal that both samples features roughly symmetrically distributed high frequency returns, with the financial crisis featuring much larger returns, both positive and negative. Hence, the 'news' in both out-of-sample periods is roughly equally positive and negative. During the financial crisis, however, the returns are much larger. The purpose of this comparison is to see how our models cope with the impact of this shift in volatility.

To formalize the discussion, let us denote by  $\widehat{RV}_{t,t+k}^m$  the forecast of volatility for horizon  $k$  with information up to time  $t$ , using model  $m$ . To recap, the models using intra-daily data directly are,  $m = SP$  for semi-parametric MIDAS, and parametric models SYMM, ASYMGJR, and ASYMLS and models that use daily volatility measures HAR-RV, HAR-RV-J, and HAR-S-RV-J. Suppose we denote the size of the estimation sample  $T_1$  and adding the two-year out-of-sample yields size  $T_2$ . For each model we compute out-of-sample the error:

$$u_{t,t+k}^m = RV_{t,t+k} - \widehat{RV}_{t,t+k}^m$$

then the two-year out-of-sample MSFE at the  $k$ -horizon is:

$$MSFE_k^m = \frac{1}{N_k} \sum_{i=1}^{N_k} (u_{t+(i-1)k,t+ik}^m)^2. \quad (4.1)$$

where  $N_k$  is the number of non-overlapping intervals of length  $k$  in the out-of-sample

period  $T_2 - T_1$ . The sample MSFE is computed for each forecasting horizon  $k$  and for each forecasting method  $m$ . The MSFE is used for the rolling sample estimates (reported in the next subsection) as well as the full-sample ones.<sup>15</sup>

In this subsection, we focus on the one-day and one-week prediction horizons, since the forecast evaluation is based on two years we do not include the monthly horizon due to the small sample size. In the next subsection we will examine monthly horizons with a statistically more elaborate procedure. Table 3 contains one day ahead forecasts for both parametric and semi-parametric model specifications. Note first of all that the differences in out-of-sample forecast performances for the 2005-2006 period are small. This is a low volatility era and all competing models produce roughly similar forecasts. Recall that for the moment we do not address whether the differences are statistically different. For the 2007-2008 sample there are two striking observations (a) the general level of MSFE is about 500 times larger (or roughly 20 times in terms of root MSFE) compared to the previous forecasting sample, and (b) the differences between models also are much more pronounced. Overall, all models do poorly, but some do much better nevertheless.

The first striking observation is that the best models - regardless of series or out-of-sample period or one-day and one-week horizon - always feature asymmetries. Unfortunately, it is not always the same model with asymmetries.

The SP model has the best forecasting performance for daily predictions of the Dow Jones and S&P 500 futures volatility series, in both cases during the financial crisis. It is also the best model for the one-day horizon cash market volatility of the S&P 500 during the financial crisis. This is quite surprising as one would have perhaps expected that in-sample data mining would penalize forecasting performance during unusual events like the crisis. Of course, the differences in performance are sometimes small - and perhaps not statistically significant. This issue will be covered later. Nevertheless, it means that a regression model involving *non-parametric* estimation of a response function applied to high-frequency data, outperforms a fully parametric model involving daily aggregate measures such as RV and even the separation of jumps and continuous path volatility. Typically, well specified parametric models outperform semi-parametric ones. Here, however, the semi-parametric models de facto use more data and are not subject to the pre-specified quadratic transformation of

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<sup>15</sup>Patton (2007) showed that when one uses the MSFE criterion, the measurement error in using a proxy (namely the sample *RV* instead of the true population integrated volatility) will not change the ranking of forecasting methods. This robustness property is not shared by some other popular forecasting evaluation methods, such as the mean absolute forecasting error (MAFE).

returns.

The most remarkable performance, however, appear to be the ASYMGJR and ASYMLS specifications which are best or nearly best for all one-day horizon predictions during the 2005-2006 period. During the financial crisis it appears to do very well for the one-week horizon - again for various series. However, the HAR-S-RV-J model is quite often the best model too at the weekly horizon, particularly during the financial crisis. Occasionally the SYMM model does well for one-week predictions.

It is also worth noting in Table 3 that models involving intra-daily data typically outperform or perform equally well compared to models using daily aggregates. This clearly shows there are advantages of using the intra-daily information directly while keeping parsimony. It is also worth noting that typically the largest gain comes from the intra-daily asymmetry - not the mere fact that RV is replaced by the symmetric SYMM specification.

The overall picture that emerges can be summarized as follows. We essentially made three types of forecasting performance comparisons. They are (1) semi-parametric with parametric models - both using high frequency data, (2) parametric models that use aggregate measures HAR-RV, and HAR-RV-J - both being implicitly *symmetric* - with a parametric model SYMM using high frequency data directly that are also symmetric, and (3) parametric models that use high frequency data and are *asymmetric* with parametric models also using high frequency data directly but are symmetric. The comparison in (3) deals with parametric mis-specification, i.e. the role played by asymmetry. The comparison (2) tells us something about loss of information due to aggregation and finally (1) reveals mis-specification of the parametric models. Our empirical findings suggest at this point that the forecasting gains are mostly due to asymmetries. The simple asymmetric high frequency data parametric models do out-perform standard models based on daily realized measures. During the financial crisis, the out-of-sample forecasting gains of asymmetric models in comparison to the standard ones range from roughly 5 % to as high as 20 % in terms of mean squared error - depending on the series and forecasting horizon . Formal statistical tests in the next subsection will show that these gains are statistically significant.

### 4.3 Are the Forecasting Gains Statistically Significant?

In the previous subsection we estimated models and appraised them over a subsequent prediction sample, and we did this for two interesting sample configurations. The out-of-sample comparisons did not involve formal tests - that is we did not provide some type of confidence intervals. To do so, we use a test proposed by Giacomini and White (2006), henceforth denoted GW, which can be viewed as a generalization, or a conditional version of the Diebold and Mariano (1995) and West (1996) tests. Another appeal of using the test is that it can handle non-nested models, which is the case in our application. In fact, Giacomini and White (2006) stress the difference between what they call forecasting methods and as opposed to forecasting models. Loosely speaking forecasting methods are the combination of estimation sample, model specification and prediction sample. This in our application most relevant, as we will not only compare models involving high frequency data directly, or daily aggregate measures, but we will also include ARCH-type models involving daily returns - i.e. the original models that were used in the literature on asymmetries in volatility. Note that original ARCH-type models are estimated via maximum likelihood - in contrast to the models discussed in the previous sections, which are regression-based. Clearly, we are dealing with a plethora of forecasting methods involving different data, models and estimation procedures. For this comparison the GW is most suited.

The GW test is implemented with a 5 year estimation window and 2 year out-of-sample forecasts. The rolling forward is implemented by truncating the earliest month of the data set and adding an additional month to the end, so that the 5 year window rolls one month at a time starting in Jan 1997-Dec 2001. We examine a rolling scheme that ends in 2006 (excluding the financial crisis) and one that ends 2008. The tests involve the sample MSFE appearing in equation (4.1), computed for each forecasting horizon  $k$ , and each forecasting model/method  $m$ . One picks a benchmark model, for which we will choose two daily realized measure models: HAR-RV-J and HAR-S-RV-J. We will call the benchmark model  $b$ . For each horizon  $k$ , the empirical efficiency of the forecasts is assessed by comparing the respective MSFEs and testing the following null hypothesis for a benchmark model against any other model  $m$  :

$$H_0 : E[(u_{t,t+k}^b)^2 - (u_{t,t+k}^m)^2 | I_{t-1}] = 0 \quad (4.2)$$

where  $I_{t-1}$  is the information set available at time  $t-1$ . In our setting we use as instruments a

constant and  $(u_{t-k,t}^b)^2$ , i.e. the most recently available MSFE. Consequently the test statistic will be  $\chi^2(1)$ .

Table 4 reports the tests of improved predictability with the HAR-RV-J as benchmark model and Table 5 reports the results for the HAR-S-RV-J benchmark. All entries in the table are p-values. Whenever an entry is boldfaced, the benchmark model is better than the alternative model. More specifically, boldfaced p-values below **0.10**, imply that the benchmark model significantly outperforms the alternative model at the 10 % or below level. All other boldfaced values imply the benchmark model still outperforms, although it is not statistically significant. All other entries imply that the alternative model outperforms the benchmark.

Looking at Table 4 we note that the HAR-RV-J model significantly outperforms the SYMM models at the daily forecast horizon for the 2001-2006 sample, but only for the SPF series when we end in 2008. All other models, including the HAR-S-RV-J outperform the benchmark for the ending 2008, and for most series ending 2006. At the weekly horizon all models typically outperform the benchmark but at the monthly horizon none do. This underscores what we discovered via the estimation of the *NIC* reported in the lower part of Figure 3 featuring symmetric news impacts at longer horizons.

When we raise the bar to the HAR-S-RV-J, reported in Table 5, we note again that the SYMM model is inferior, whereas in particular the ASYMGJR model featuring asymmetries and using intra-daily data outperforms the benchmark model for the evaluation sample ending 2006. Adding the crisis the evidence weakens the evidence against the ASYMLS specification and the ASYMGJR model remains significantly better at the 5 %. At the weekly horizon this also holds except for the DJF series (ending 2006) and for the DJC and SPF series when the crisis is added.

Recall that the GW procedure can handle non-nested models, or more general, a diverse set of forecasting methods that are different combinations of estimation sample, model specification and prediction sample. This generality allows us also to include standard daily GARCH models, and compare them with a benchmark model involving high frequency data. Therefore, we conclude this section with a comparison of a symmetric model based on high frequency data, namely the HAR-RV-J model featured as benchmark in Table 4 and the original GJR model of Glosten, Jagannathan, and Runkle (1993) using daily return series for the daily prediction horizon, weekly returns for the same horizon and similar for the

monthly one.<sup>16</sup> This implies that, say, daily volatility forecasts are compared with high frequency realized volatility measures - i.e. the same realized series to appraise the other models. The lower panel in the table reports the test statistic results. They clearly show the advantages of using high frequency data, even though the GJR features asymmetries, the daily data is 'too noisy' to provide predictions that outperform the high frequency symmetric benchmark model. The gains achieved by using high frequency data have been abundantly emphasized in the literature. The original daily return GARCH literature emphasized the importance of asymmetries - using daily returns only. The contribution of our paper is to show that asymmetry remains important, but it requires models suitable to handle high frequency data.

The picture that emerges is that asymmetric intra-daily ASYMGJR model outperforms symmetric and asymmetric daily realized measure models - except at the monthly horizon. To reinforce this conclusion we turn our attention to Table 6 where we reversed the role of benchmark, i.e. we use the ASYMGJR model as benchmark. Using the same convention as in the previous tables, we should expect boldfaced low p-values. That is indeed the case for the 2001-2006 sample appearing in the top panel - except at some of the monthly horizon forecasts entries. Note that for one-day ahead forecasts all p-values are zero and boldfaced. This means that none of the alternative models significantly outperform the ASYMGJR. At the one-week all entries are boldfaced again, yet some indicate that the ASYMGJR model is not statistically significantly better at forecasting. Most p-values are nevertheless below the 5 % threshold. At the monthly horizon there is clearly no dominance of the ASYMGJR model - as noted before. When we turn to the lower panel - which includes the financial crisis - the one-day ahead evidence is somewhat weaker - but still all entries are boldfaced and at 10 % the ASYMGJR is better than HAR-RV-J, HAR-S-RV-J and SYMM for two out of four series. The other p-values are slightly above 10 % with the exception of DJC with the ASYMLS model. At the one-week horizon there is a similar pattern, but here we note that for one series - SPF - the SYMM model appears to be statistically significantly better than the ASYMGJR one.

While the ASYMGJR model dominates at the one-day and one-week prediction horizon, we also note again that at the monthly horizon this is no longer the case. At the monthly horizon, it seems that the existing models - the simplest being the HAR-RV-J model - performs as

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<sup>16</sup>This means we deal with direct forecasts, as opposed to iterated forecasts - iterating forward the daily ones - for the weekly and monthly horizon. For further discussion of iterated versus direct forecasts of volatility, see e.g. Ghysels, Valkanov, and Rubia (2009).

good as any of the more sophisticated ones. Hence, asymmetries matter for forecasting at short horizons, but become less relevant for the monthly horizon. This implies that asymmetries matter for typical risk management horizons (say e.g. value-at-risk analysis) but do not matter so much for longer term asset allocation decisions.

## 5 Conclusions

The paper has two contributions: (1) we show asymmetry matters for volatility forecasting and (2) we show that relatively simple parametric models, sharing features with the original work of Glosten, Jagannathan, and Runkle (1993) but using instead intra-daily returns, outperform models with daily realized variance and semi-variance measures in terms of out-of-sample forecasting - particularly during turbulent volatility periods such as the most recent financial crisis.

The writing of Engle and Ng (1993) was in part motivated by the recognition that volatility models, including the at time very popular daily GARCH(1,1) model, imposed a symmetric response function of shocks to volatility and that most often such response was probably misspecified. The most preferred model of Engle and Ng (1993), based on their empirical analysis, was that of Glosten, Jagannathan, and Runkle (1993). The main findings of this literature still remain very much part of our core beliefs today regarding the key stylized facts of volatility dynamics. Namely, it is widely believed that “*good*” news and “*bad*” news do not have the same impact on future volatility. This is a theme that resonates in many empirical asset pricing papers, including Campbell and Hentschel (1992), Glosten, Jagannathan, and Runkle (1993), among many others.

Our empirical results clearly show that the findings from the daily volatility models remain important for high frequency data. Moderately good (intra-daily) news reduces volatility (the next day), while both very good news (unusual high positive returns) and bad news (negative returns) increase volatility, with the latter having a more severe impact. We also find that the asymmetry evaporates at longer horizons - news impacts are symmetric at the one month horizon. This implies that asymmetries matter for typical risk management horizons (say e.g. value-at-risk analysis) but do not matter so much for longer term asset allocation decisions.

Parametric specifications, which bridge the new and old literature, confirm these findings

of asymmetry - particularly at shorter horizons - via simple hypotheses imposed on the parameters. Relatively simple asymmetric high frequency data parametric models outperform models with daily realized variance and semi-variance measures in terms of out-of-sample forecasting - particularly during turbulent volatility periods such as the most recent financial crisis, where the out-of-sample forecasting gains of asymmetric models in comparison to the standard ones range from roughly 5 % to as high as 20 % in terms of mean squared error - depending on the series and forecasting horizon. Formal statistical tests show that these gains are statistically significant.

## Technical Appendix

### A Asymptotic properties of semi-parametric MIDAS regression models

It will be useful to consider a generic setting. In such a setting we consider a regression model involving a low frequency regressand  $y$  and regressors  $x$ , sampled more frequently with a parametric lag structure for temporal dependence and a nonparametric function  $m(\cdot)$ . Note that we use a simplified notation, slightly different from the main body in the paper, as it makes the technical results easier to summarize. The regression is written:

$$y_t = \sum_{j=1}^{\tau} B_j(\theta) m(x_{t-1-(j-1)/M}) + \varepsilon_t \quad (\text{A.3})$$

where the residuals  $\varepsilon_t$  are a martingale difference sequence. The lag coefficients  $B_j(\cdot)$ ,  $j = 1, \dots, \tau$ , are described by a finite dimensional parameter  $\theta \in \Theta \subset \mathbb{R}^p$  with  $\sum_{j=1}^{\tau} B_j(\theta) = 1$  for identification. Moreover, without loss of generality, we assume  $\tau = nM$ ,  $n \in \mathbb{N}$ .

Note that this setting easily translate into equation (3.1), namely  $y = RV_{t,t+1}$ , the returns  $r_{t-j,i\Delta}$  are the regressors  $x$ , sampled  $M = 1/\Delta$  times, the polynomial lag  $B_j(\theta)$  is  $\psi_{ij}(\theta)$  and finally  $NIC$  is the function  $m$ . We impose the following key assumption:

**Assumption A.1** *The process  $\{x_{s/M}\}_{s=-\infty}^{+\infty}$  is stationary; and the processes  $\{y_t, x_{t-j/M}\}_{t=-\infty}^{+\infty}$  for  $j = 1, \dots, M$  are jointly stationary and geometrically  $\alpha$ -mixing and  $\alpha(k) \leq a\bar{s}^k$  for some constant  $a$  and  $0 \leq \bar{s} < 1$  when  $k$  is big enough.*

The true parameters  $\theta_0$  and the true function  $m_0(\cdot)$  are defined as the minimizers of the population least squares criterion function

$$S(\theta, m) = E \left[ \left\{ y_t - \sum_{j=1}^{\tau} B_j(\theta) m(x_{t-1-(j-1)/M}) \right\}^2 \right] \quad (\text{A.4})$$

Define  $m_\theta$  as the minimizer of the criterion function for any given  $\theta \in \Theta$ . A necessary condition for  $m_\theta$  to be the minimizer of (A.4) is that it satisfies the first order condition

$$E \left[ \left\{ y_t - \sum_{j=1}^{\tau} B_j(\theta) m(x_{t-1-(j-1)/M}) \right\} \sum_{k=1}^{\tau} B_k(\theta) g(x_{t-1-(k-1)/M}) \right] = 0 \quad (\text{A.5})$$

for any measurable (and smooth) function  $g$  yielding a well-defined expectation. Moreover, the second order condition is  $-E \left[ \left\{ \sum_{k=1}^{\tau} B_k(\theta) g(x_{t-1-(k-1)/M}) \right\}^2 \right]$ . The fact that the latter is negative implies that the

solution of the first order condition does indeed (locally) minimize the criterion. The first order condition (A.5) can be rewritten as

$$\begin{aligned} \sum_{k=1}^{\tau} B_k(\theta) E[y_t g(x_{t-1-(k-1)/M})] &= \sum_{k=1}^{\tau} \sum_{j=1, j \neq k}^{\tau} B_k(\theta) B_j(\theta) E[m_{\theta}(x_{t-1-(j-1)/M}) g(x_{t-1-(k-1)/M})] \\ &= \sum_{k=1}^{\tau} B_k(\theta)^2 E[m_{\theta}(x_{t-1-(k-1)/M}) g(x_{t-1-(k-1)/M})] \end{aligned}$$

Taking  $g(\cdot)$  to be the Dirac delta function, we have that

$$\begin{aligned} \sum_{k=1}^{\tau} B_k(\theta) E[y_t | x_{t-1-(k-1)/M} = x] &= \sum_{k=1}^{\tau} \sum_{j=1, j \neq k}^{\tau} B_k(\theta) B_j(\theta) E[m_{\theta}(x_{t-1-(j-1)/M}) | x_{t-1-(k-1)/M} = x] \\ &= \sum_{k=1}^{\tau} B_k(\theta)^2 m_{\theta}(x) \end{aligned}$$

for each  $x$ . This is an implicit equation for  $m_{\theta}(\cdot)$  which can be re-expressed as a linear type two integral equation in  $L_2(f_0)$ , where  $f_0$  is the marginal density of  $x_{s/M}$ . Define  $B_k^*(\theta) = B_k(\theta) / \sum_{j=1}^{\tau} B_j(\theta)^2$ ,  $k = 1, \dots, \tau$ , and  $B_i^+(\theta) = \sum_{k=1}^{\tau-|i|} B_k(\theta) B_{k+|i|}(\theta) / \sum_{j=1}^{\tau} B_j(\theta)^2$ ,  $i = \pm 1, \dots, \pm(\tau-1)$ . Finally, let  $f_{0,j}$  be the joint density of  $(x_{s/M}, x_{(s-j)/M})$ , then:

$$m_{\theta}(x) = m_{\theta}^*(x) + \int H_{\theta}(x, y) m_{\theta}(y) f_0(y) dy, \text{ or } m_{\theta} = m_{\theta}^* + H_{\theta} m_{\theta}, \quad (\text{A.6})$$

$$m_{\theta}^*(x) = \sum_{k=1}^{\tau} B_k^*(\theta) E[y_t | x_{t-1-(k-1)/M} = x] \quad (\text{A.7})$$

$$H_{\theta}(x, y) = - \sum_{i=\pm 1}^{\pm(\tau-1)} B_i^+(\theta) \frac{f_{0,i}(y, x)}{f_0(y) f_0(x)}. \quad (\text{A.8})$$

where the sum in (A.8) runs from  $i = 1 - \tau, \dots, \tau - 1$ , excluding 0 (using the same notation as in Linton and Mammen (2005)). Note also that  $m_0 = m_{\theta_0}$ . The general estimation strategy for a given sample  $\{\{y_t\}_{t=1}^T, \{x_{s/M}\}_{s=1}^{MT}\}$  is (a) for each  $\theta$  compute estimators  $\hat{m}_{\theta}^*, \hat{H}_{\theta}$  of  $m_{\theta}^*, H_{\theta}$ , (b) solve an empirical version of (A.6) to obtain an estimator  $\hat{m}_{\theta}$  of  $m_{\theta}$  and (c) choose  $\hat{\theta}$  to minimize the profiled least squares criterion with respect to  $\theta$  and let  $\hat{m}(x) = \hat{m}_{\hat{\theta}}(x)$ . The practical implementation of the above estimator is basically the same as in Linton and Mammen (2005), and therefore omitted.

Define the functions  $\beta_{\theta}^j(x)$ ,  $j = 1, 2$ , as solutions to the integral equations  $\beta_{\theta}^j = \beta_{\theta}^{*,j} + H_{\theta} \beta_{\theta}^j$ , in which:

$$\begin{aligned} \beta_{\theta}^{*,1}(x) &= m_{\theta}^{*''}(x), \\ \beta_{\theta}^{*,2}(x) &= \sum_{i=\pm 1}^{\pm(\tau-1)} B_i^*(\theta) \left\{ E(m_{\theta}(x_{(s-i)/M}) | x_{s/M} = x) \frac{f_0''(x)}{f_0(x)} - \int [\nabla_2 f_{0,s}(x, y)] \frac{m_{\theta}(y)}{f_0(x)} dy \right\} \end{aligned}$$

where the operator  $\nabla_2$  is defined as  $\nabla_2 = \partial^2/\partial x^2 + \partial^2/\partial y^2$ . Then define

$$\omega_\theta(x) = \frac{\|K\|_2^2}{f_0(x)} \text{var}[\eta_{\theta,s} + \zeta_{\theta,s}] \quad (\text{A.9})$$

$$b_\theta(x) = \frac{1}{2} \mu_2(K) [\beta_\theta^1(x) + \beta_\theta^2(x)] \quad (\text{A.10})$$

Define:

$$\begin{aligned} \omega(x) &= \frac{\|K\|_2^2 \sum_{j=1}^{\tau} B_j^2(\theta_0) E[\varepsilon_t^2 | x_{t-1-(j-1)/M} = x]}{f_0(x) \left[ \sum_{j=1}^{\tau} B_j^2(\theta_0) \right]^2} \\ &+ \frac{M-1}{M} \frac{\|K\|_2^2 \sum_{j=1}^{\tau} \sum_{k=1, k \neq j}^{\tau} B_j^2(\theta_0) B_k^2(\theta_0) \text{var}(m(x_{t+(j-k)/M}) | x_t = x)}{f_0(x) \left( \sum_{j=1}^{\tau} B_j^2(\theta_0) \right)^2} \end{aligned} \quad (\text{A.11})$$

$$b(x) = \mu_2(K) \left\{ \frac{1}{2} m''(x) + (I - H_\theta)^{-1} \left[ \frac{f'_0}{f_0} \frac{\partial}{\partial x} (H_\theta m) \right] (x) \right\} \quad (\text{A.12})$$

Let  $\varepsilon_t(\theta) = y_t - \sum_{j=1}^{\tau} B_j(\theta) m_\theta(x_{t-1-(j-1)/M})$ , and let

$$\Sigma = \left\{ E \left[ \frac{\partial^2 \varepsilon_t}{\partial \theta \partial \theta^\tau}(\theta_0) \right] \right\}^{-1} E \left[ \frac{\partial \varepsilon_t}{\partial \theta} \frac{\partial \varepsilon_t}{\partial \theta^\tau} \varepsilon_t^2(\theta_0) \right] \left\{ E \left[ \frac{\partial^2 \varepsilon_t}{\partial \theta \partial \theta^\tau}(\theta_0) \right] \right\}^{-1} \quad (\text{A.13})$$

The following theorem establishes the asymptotic properties of the semi-parametric MIDAS regression model:

**Theorem A.1** *Suppose that Assumption A.1 and the regularity conditions appearing in Chen, Ghysels, and Renault (2009) hold. Then for each  $\theta \in \Theta$  and  $x \in (\underline{x}, \bar{x})$*

$$\sqrt{Th} [\hat{m}_\theta(x) - m_\theta(x) - h^2 b_\theta(x)] \rightarrow N(0, \omega_\theta(x))$$

Moreover,

$$\sqrt{T}(\hat{\theta} - \theta_0) \rightarrow N(0, \Sigma)$$

Furthermore, for  $x \in (\underline{x}, \bar{x})$

$$\sqrt{Th}(\hat{m}(x) - m(x) - h^2 b(x)) \rightarrow N(0, \omega(x))$$

where  $h$  denotes the bandwidth,  $\Sigma$  (eq. (A.13)) is variance matrix,  $b$  (eq. (A.12)) and  $b_\theta$  (eq. (A.10)) are bias functions,  $\omega$  appears below and  $\omega_\theta$  (eq. (A.9)) are variance functions.

In particular,

$$\begin{aligned} \omega(x) = & \frac{\|K\|_2^2 \sum_{j=1}^{\tau} B_j^2 E[\varepsilon_t^2 | x_{t-1-(j-1)/M} = x]}{f_0(x) \left( \sum_{j=1}^{\tau} B_j^2 \right)^2} \\ & + \frac{M-1}{M} \frac{\|K\|_2^2 \sum_{j=1}^{\tau} \sum_{k=1, k \neq j}^{\tau} B_j^2 B_k^2 \text{var}(m(x_{t+(j-k)/M}) | x_t = x)}{f_0(x) \left( \sum_{j=1}^{\tau} B_j^2 \right)^2} \end{aligned} \quad (\text{A.14})$$

The above expression shows that the mixed data sampling scheme in semi-parametric MIDAS regressions adds an extra term, i.e. the last appearing in the above expression. When  $M = 1$ , the asymptotic distribution collapses to the case covered in Linton and Mammen (2006). When  $M > 1$ , the dependent variable is sampled less frequent than the regressor which - compared to the case where all processes are sampled at the frequency  $1/M$ , implies that  $(M - 1)/M$  regression equations are missing.

Finally, to calculate the confidence interval, we assume: (1) the sample size is large enough, so the variance of  $\hat{m}(x)$  is the same as the asymptotic variance; (2)  $\text{var}(m(x_{s/M}) | x_{k/M} = x) = \text{var}(m(x_{s/M}))$ ,  $\forall s \neq k$ ; (3)  $\text{var}(\varepsilon_t | x_{t-j/M} = x) = \text{var}(\varepsilon_t)$ ,  $j = 1, \dots, \tau$ . The confidence interval is then calculated for any  $x$  as,

$$\begin{aligned} CI(x) = & [\hat{m}(x) + Z_{\alpha} \hat{s}(x), \hat{m}(x) + Z_{1-\alpha} \sqrt{\hat{s}(x)}] \\ \hat{s}(x) = & \frac{\|K\|_2^2}{Th \hat{f}_0(x) \sum_{j=1}^{\tau} B_j^2(\hat{\theta})} \left( \text{var}(\hat{\varepsilon}_t) + \frac{M-1}{M} \frac{\sum_{j=1}^{\tau} \sum_{k=1, k \neq j}^{\tau} B_j^2(\hat{\theta}) B_k^2(\hat{\theta})}{\sum_{j=1}^{\tau} B_j^2(\hat{\theta})} \text{var}(\hat{m}(x_t)) \right) \end{aligned} \quad (\text{A.15})$$

where  $Z_{\alpha}$  is the  $\alpha$ -quantile of the standard normal distribution. We set  $\alpha = 0.05$ , so that  $Z_{0.05} = -1.645$  and  $Z_{0.95} = 1.645$ .<sup>17</sup>

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<sup>17</sup>Note that we are computing the confidence interval of  $\hat{m}(x)$  corresponding to  $E(\hat{m}(x))$  instead of  $m_0(x)$ , so we omit the discussion related to the bias part. See Wasserman (2006, p.89) for more details related to the confidence interval of nonparametric estimation.

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**Table 1: Details of the Data Series and Model Acronyms**

The top part of the table provides the details of the data used in our study. We analyze four series which consist of intra-day returns of respectively Dow Jones and S&P 500 cash and futures markets. To lower part summarizes all models, showing the equation numbers, the models' acronyms and some details. The generic specification appears in equation (3.1), namely:  $RV_{t,t+1} = \psi_0 + \sum_{j=1}^{\tau} [\sum_{i=1}^{\Delta^{-1}} \psi_{ij}(\theta)NIC(r_{t-j,i\Delta})] + \varepsilon_{t,t+1}$ , where  $\sum_{j=1}^{\tau} \sum_{i=1}^{\Delta^{-1}} \psi_{ij} = 1$  and  $NIC(r)$  stands for news impact curve.

|                                       |                        | Period   | Days                      | Trading Hours (EST) | $\Delta^{-1}$       |
|---------------------------------------|------------------------|--|---------------------------|---------------------|---------------------|
| Full Sample                           |                        |  |                           |                     |                     |
| Dow Jones                             | Cash                   | <i>DJC</i>   | 04/01/1993 – 12/31/2008   | 3969                | 9 : 30 – 16 : 00 78 |
|                                       | Futures                | <i>DJF</i>   | 10/06/1997 – 12/31/2008   | 2834                | 9 : 30 – 16 : 00 78 |
| S&P 500                               | Cash                   | <i>SPC</i>   | 09/30/1985 – 12/31/2008   | 5668                | 9 : 30 – 16 : 00 78 |
|                                       | Futures                | <i>SPF</i>   | 04/21/1982 – 12/31/2008   | 6764                | 9 : 30 – 16 : 00 78 |
| News Impact                           |                        |  |                           |                     |                     |
|                                       | Acronym                | Explanation  |                           |                     |                     |
| Intra-daily returns - Parametric      |                        |  |                           |                     |                     |
|                                       | $br^2$                 | SYMM   | Symmetric NIC             |                     |                     |
|                                       | $(br^2 + c1_{r<0}r^2)$ | ASYMGJR  | Asymmetric GJR            |                     |                     |
|                                       | $((r - c)^2)$          | ASYMLS   | Asymmetric Location Shift |                     |                     |
| Intra-daily returns - Semi-parametric |                        |  |                           |                     |                     |
| Non-parametric NIC                    | SP                     | Semi-parametric MIDAS appearing in Eq. (3.1)       |                           |                     |                     |
| Models with daily volatility          |                        |  |                           |                     |                     |
|                                       | HAR-RV                 | Eq. (2.4) using RV regressors                      |                           |                     |                     |
|                                       | HAR-RV-J               | Eq. (2.5) using BPV and Jump regressors            |                           |                     |                     |
|                                       | HAR-S-RV-J             | Eq. (2.7) using semi-variances and Jump regressors |                           |                     |                     |

**Table 2: Asymmetry and Parameter Estimates**

Panel A pertains to the regression appearing in (2.7) involving semi-variances. Entries pertain to tests of the single restrictions that either the daily, weekly, or monthly semi-variances have equal coefficients. The final column contains a joint test of the null with all three restrictions. The asymptotic variances to compute the tests use HAC standard errors with lag lengths that match the inference recommendations of Andersen, Bollerslev, and Diebold (2007). Panel B pertains to parametric models using intra-daily returns and featuring asymmetries. The panel displays the parameter estimates of the lag polynomials involving parameters  $\theta_1$  through  $\theta_4$ , see equation (3.2). The parameters  $a$ ,  $b$ , and  $c$ , determine the news impact, where  $c$  relates to asymmetries, since for the ASYMGJR model  $NIC(r) = (br^2 + c1_{r<0}r^2)$ , and for the ASYMLS model  $NIC(r) = (b(r - c)^2)$ . The parameter estimates are reported for one representative series, the S&P 500 Futures contract, at one day and one week forecast horizons. Entries in Panel A are p-values, since joint and single restriction tests feature different asymptotic distributions. Finally, all the results in the table pertain to full sample estimates. The latter differ across series due to data availability - see Table 1 for details.

|                     |         | Panel A |        |         |       |
|---------------------|---------|---------|--------|---------|-------|
| Regressors          |         | Daily   | Weekly | Monthly | Joint |
| Dow Jones - Cash    |         |         |        |         |       |
| Horizon             | Daily   | 0.49    | 0.35   | 0.92    | 0.37  |
|                     | Weekly  | 0.06    | 0.29   | 0.01    | 0.00  |
|                     | Monthly | 0.00    | 0.42   | 0.00    | 0.00  |
| Dow Jones - Futures |         |         |        |         |       |
|                     | Daily   | 0.13    | 0.16   | 0.02    | 0.00  |
|                     | Weekly  | 0.09    | 0.01   | 0.66    | 0.00  |
|                     | Monthly | 0.02    | 0.83   | 0.00    | 0.00  |
| S&P Cash            |         |         |        |         |       |
|                     | Daily   | 0.05    | 0.09   | 0.81    | 0.00  |
|                     | Weekly  | 0.16    | 0.41   | 0.04    | 0.00  |
|                     | Monthly | 0.00    | 0.12   | 0.73    | 0.00  |
| S&P Futures         |         |         |        |         |       |
|                     | Daily   | 0.11    | 0.25   | 0.03    | 0.00  |
|                     | Weekly  | 0.00    | 0.02   | 0.12    | 0.00  |
|                     | Monthly | 0.10    | 0.63   | 0.00    | 0.00  |

Table continued on next page ...

Table 2 continued

## Panel B

|   | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $a$       | $b$      | $c$        |
|---|------------|------------|------------|------------|-----------|----------|------------|
| S&P 500 Futures Market - One-day horizon  |            |            |            |            |           |          |            |
| ASYMGJR                                   | 2.337e-014 | 3.051      | 1.360      | 1.955      | -0.008254 | -125.9   | 428.5      |
| (std. dev.)                               | (0.005456) | (0.03413)  | (0.001195) | (0.004495) | (0.01655) | (4.728)  | (10.08)    |
| ASYMLS                                    | 2.337e-014 | 1.974      | 1.239      | 2.825      | -39.18    | 67.61    | 0.7621     |
| (std. dev.)                               | (0.004674) | (0.0215)   | (0.002814) | (0.01108)  | (0.4254)  | (0.7221) | (0.001995) |
| S&P 500 Futures Market - One-week horizon |            |            |            |            |           |          |            |
| ASYMGJR                                   | 0.6527     | 2.672      | 1.740      | 1.347      | -0.01653  | -272.3   | 727.2      |
| (std. dev.)                               | (0.02066)  | (0.1054)   | (0.01897)  | (0.01655)  | (0.02881) | (16.51)  | (34.28)    |
| ASYMLS                                    | 1.614e-013 | 0.6246     | 78.65      | 148.1      | -0.08167  | 80.52    | 0.05015    |
| (std. dev.)                               | (0.01403)  | (0.01892)  | (1.300)    | (2.554)    | (0.02946) | (1.580)  | (0.004611) |

**Table 3: Out-of-sample performance of Semi-Parametric and Parametric MIDAS regression models**

The table shows the out-of-sample *MSFE* of the SP, i.e. the semi-parametric MIDAS model, and parametric models SYMM, ASYMGJR, and ASYMLS and models that use daily volatility measures HAR-RV, HAR-RV-J, and HAR-S-RV-J. The *MSFE* of the SP model is the benchmark. All other models are reported relative to the benchmark, namely values below one outperform the benchmark. We consider two sample configurations, one ending in 2004 and out-of-sample appraisal 2005-2006, the other ending in 2006 and out-of-sample appraisal 2007-2008. *DJC* stands for Dow Jones Cash Market, *DJF* for Dow Jones Futures Market, *SPC* for S&P 500 Cash Market, and *SPF* for S&P 500 Futures Market.

|            |                      | One-day ahead forecasts              |            |            |            | One-week ahead forecasts |            |            |            |
|------------|----------------------|--------------------------------------|------------|------------|------------|--------------------------|------------|------------|------------|
|            |                      | <i>DJC</i>                           | <i>DJF</i> | <i>SPC</i> | <i>SPF</i> | <i>DJC</i>               | <i>DJF</i> | <i>SPC</i> | <i>SPF</i> |
|            | Out-of-sample Period | Semi-Parametric Intra-daily returns  |            |            |            |                          |            |            |            |
| SP         | 2005-2006            | 0.04                                 | 0.05       | 0.04       | 0.07       | 0.02                     | 0.05       | 0.03       | 0.08       |
|            | 2007-2008            | 19.99                                | 9.63       | 16.32      | 11.28      | 16.94                    | 4.60       | 20.52      | 6.96       |
|            |                      | Parametric Intra-daily returns       |            |            |            |                          |            |            |            |
| SYMM       | 2005-2006            | 1.00                                 | 1.00       | 1.00       | 0.57       | 1.50                     | 1.40       | 0.67       | 0.25       |
|            | 2007-2008            | 0.95                                 | 1.10       | 1.79       | 2.88       | 0.79                     | 1.19       | 0.60       | 3.67       |
| ASYMGJR    | 2005-2006            | 0.75                                 | 0.60       | 0.75       | 0.72       | 1.00                     | 1.40       | 0.67       | 0.25       |
|            | 2007-2008            | 0.95                                 | 1.41       | 1.11       | 1.29       | 0.67                     | 1.11       | 0.42       | 6.72       |
| ASYMLS     | 2005-2006            | 1.25                                 | 1.20       | 0.57       | 1.29       | 1.50                     | 1.40       | 0.67       | 0.38       |
|            | 2007-2008            | 0.91                                 | 1.02       | 1.01       | 1.12       | 0.73                     | 0.95       | 0.48       | 3.67       |
|            |                      | Parametric Daily Volatility Measures |            |            |            |                          |            |            |            |
| HAR-RV     | 2005-2006            | 1.25                                 | 1.00       | 1.75       | 0.57       | 3.00                     | 1.60       | 3.00       | 0.63       |
|            | 2007-2008            | 1.04                                 | 1.13       | 1.08       | 1.17       | 1.06                     | 1.17       | 0.59       | 1.00       |
| HAR-RV-J   | 2005-2006            | 1.00                                 | 0.80       | 0.86       | 2.00       | 1.20                     | 0.80       | 2.33       | 0.63       |
|            | 2007-2008            | 1.02                                 | 1.09       | 1.12       | 1.22       | 1.02                     | 0.85       | 0.60       | 0.99       |
| HAR-S-RV-J | 2005-2006            | 1.00                                 | 0.60       | 1.00       | 0.43       | 1.50                     | 0.40       | 1.00       | 0.50       |
|            | 2007-2008            | 1.08                                 | 0.98       | 1.02       | 1.04       | 1.03                     | 0.84       | 0.53       | 0.97       |

**Table 4: Tests of Improved Predictability: HAR-RV-J Benchmark**

The table reports the conditional forecasting ability test of Giacomini and White for each model against the benchmark HAR-RV-J model appearing in equation (2.5). The model acronyms appear in lower panel of Table 1, except for the GJR entry which pertains to the original specification of Glosten, Jagannathan, and Runkle (1993) with daily data. The tests involve the sample MSFE appearing in equation (4.1), computed for each forecasting horizon  $k$ , and each forecasting model/method  $m$ . The null hypothesis appears in equation (4.2) with instruments a constant and  $u_{t-k,t}^b$ . The entries are  $\chi^2(1)$  distributed test statistics. *DJC* stands for Dow Jones Cash Market, *DJF* for Dow Jones Futures Market, *SPC* for S&P 500 Cash Market, and *SPF* for S&P 500 Futures Market. All entries are p-values. Whenever an entry is boldfaced, the benchmark model is better than the alternative model, implying that the benchmark model significantly outperforms the alternative model. Normal-faced entries with low p-values mean that the alternative model significantly outperforms the benchmark. The tests involve rolling 5-year samples for estimation and 2-year out-of-sample forecast performances rolling over one month at the time - starting with the 1997-2001 estimation sample.

|            | One-day ahead forecasts      |             |             |             | One-week ahead forecasts |             |             |             | One-month ahead forecasts |             |             |             |
|------------|------------------------------|-------------|-------------|-------------|--------------------------|-------------|-------------|-------------|---------------------------|-------------|-------------|-------------|
|            | <i>DJC</i>                   | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  | <i>DJC</i>               | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  | <i>DJC</i>                | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  |
|            | Evaluation sample: 2001-2006 |             |             |             |                          |             |             |             |                           |             |             |             |
| HAR-S-RV-J | 0.00                         | 0.00        | 0.00        | <b>0.00</b> | 0.00                     | 0.01        | 0.02        | 0.01        | <b>0.29</b>               | 0.13        | 0.19        | 0.29        |
| SYMM       | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | 0.01                     | 0.08        | 0.02        | 0.01        | 0.19                      | 9.16        | 0.14        | 0.14        |
| ASYMGJR    | 0.00                         | 0.00        | 0.00        | 0.00        | 0.01                     | 0.03        | 0.00        | 0.00        | 0.17                      |             | 0.15        | 0.13        |
| ASYMLS     | 0.00                         | <b>0.00</b> | 0.00        | <b>0.00</b> | 0.03                     | 0.08        | 0.02        | 0.01        | 0.18                      | 0.22        | 0.16        | 0.13        |
| GJR        | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.00</b>              | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.00</b>               | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> |
|            | Evaluation sample: 2001-2008 |             |             |             |                          |             |             |             |                           |             |             |             |
| HAR-S-RV-J | 0.01                         | 0.00        | 5.70        | 0.02        | 0.09                     | 0.00        | 0.29        | 0.01        | <b>0.10</b>               | <b>0.37</b> | <b>0.29</b> | <b>0.11</b> |
| SYMM       | 0.01                         | 0.03        | 0.04        | <b>0.02</b> | 0.01                     | 0.02        | 0.01        | 0.04        | 0.09                      | 0.18        | 0.10        | <b>0.19</b> |
| ASYMGJR    | 0.02                         | 0.01        | 0.02        | 0.04        | 0.01                     | 0.00        | 0.02        | 0.04        | <b>0.26</b>               | 0.23        | 0.10        | <b>0.15</b> |
| ASYMLS     | 0.02                         | 0.02        | 0.02        | 0.05        | 0.01                     | 0.02        | 0.02        | 0.04        | 0.11                      | 0.09        | 0.11        | 0.14        |
| GJR        | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.00</b>              | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.00</b>               | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> |

**Table 5: Tests of Improved Predictability: HAR-S-RV-J Benchmark**

The table reports the conditional forecasting ability test of Giacomini and White for each model against the benchmark HAR-S-RV-J model appearing in equation (2.7). The model acronyms appear in lower panel of Table 1. The tests involve the sample MSFE appearing in equation (4.1), computed for each forecasting horizon  $k$ , and each forecasting model/method  $m$ . The null hypothesis appears in equation (4.2) with instruments a constant and  $u_{t-k,t}^b$ . The entries are test statistic will be  $\chi^2(1)$ . *DJC* stands for Dow Jones Cash Market, *DJF* for Dow Jones Futures Market, *SPC* for S&P 500 Cash Market, and *SPF* for S&P 500 Futures Market. All entries are p-values. Whenever an entry is boldfaced, the benchmark model is better than the alternative model, implying that the benchmark model significantly outperforms the alternative model. Normal-faced entries with low p-values mean that the alternative model significantly outperforms the benchmark. The tests involve rolling 5-year samples for estimation and 2-year out-of-sample forecast performances rolling over one month at the time - starting with the 1997-2001 estimation sample.

|         | One-day ahead forecasts      |             |             |             | One-week ahead forecasts |             |            |             | One-month ahead forecasts |            |            |             |
|---------|------------------------------|-------------|-------------|-------------|--------------------------|-------------|------------|-------------|---------------------------|------------|------------|-------------|
|         | <i>DJC</i>                   | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  | <i>DJC</i>               | <i>DJF</i>  | <i>SPC</i> | <i>SPF</i>  | <i>DJC</i>                | <i>DJF</i> | <i>SPC</i> | <i>SPF</i>  |
|         | Evaluation sample: 2001-2006 |             |             |             |                          |             |            |             |                           |            |            |             |
| SYMM    | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | 0.01                     | <b>0.16</b> | 0.10       | 0.14        | 0.21                      | 0.26       | 0.18       | 0.13        |
| ASYMGJR | 0.00                         | 0.00        | 0.00        | 0.00        | 0.01                     | <b>0.11</b> | 0.01       | 0.03        | 0.19                      | 0.19       | 0.19       | 0.13        |
| ASYMLS  | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | 0.07                     | <b>0.15</b> | 0.11       | 0.15        | 0.21                      | 0.19       | 0.21       | <b>0.13</b> |
|         | Evaluation sample: 2001-2008 |             |             |             |                          |             |            |             |                           |            |            |             |
| SYMM    | 0.03                         | <b>0.00</b> | 0.11        | <b>0.00</b> | 0.01                     | 0.06        | 0.02       | <b>0.06</b> | 0.09                      | 0.15       | 0.11       | 0.21        |
| ASYMGJR | 0.03                         | 0.06        | 0.03        | 0.04        | <b>0.01</b>              | 0.02        | 0.02       | <b>0.06</b> | 0.15                      | 0.13       | 0.11       | 0.25        |
| ASYMLS  | 0.02                         | <b>0.00</b> | 0.04        | 0.09        | 0.02                     | 0.07        | 0.03       | <b>0.06</b> | 0.11                      | 0.14       | 0.12       | 0.26        |

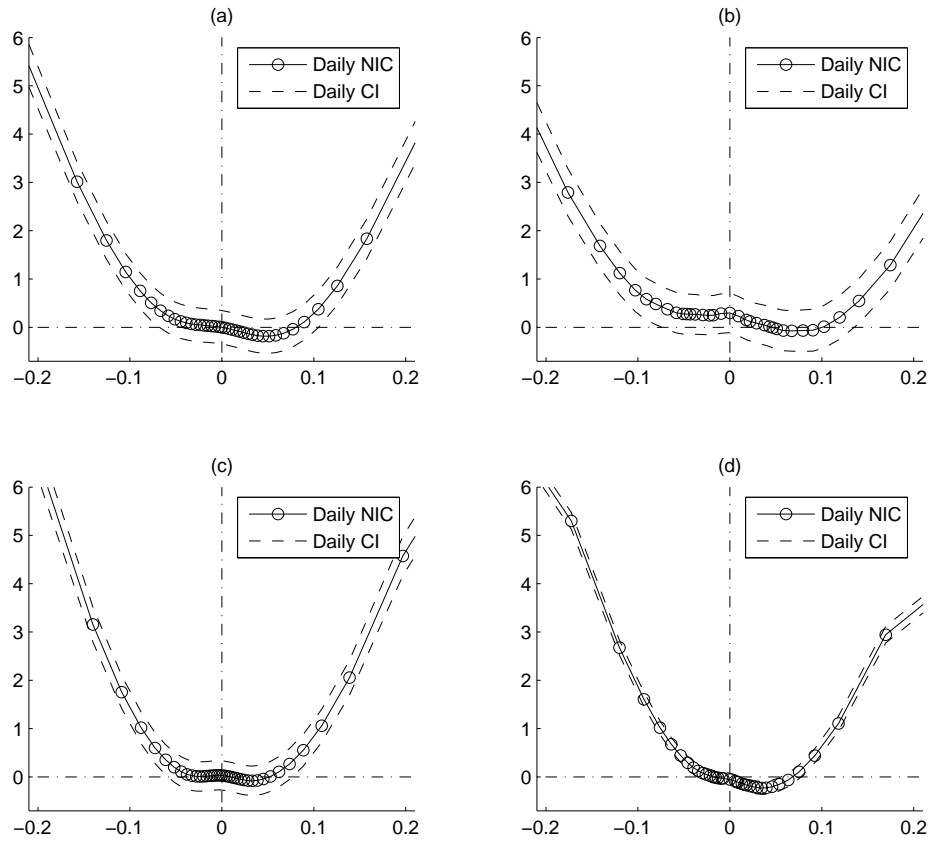
**Table 6: Tests of Improved Predictability: ASYMGJR Benchmark**

The table reports the conditional forecasting ability test of Giacomini and White for each model against the benchmark ASYMGJR model appearing in subsection 3.1. The model acronyms appear in lower panel of Table 1. The tests involve the sample MSFE appearing in equation (4.1), computed for each forecasting horizon  $k$ , and each forecasting model/method  $m$ . The null hypothesis appears in equation (4.2) with instruments a constant and  $u_{t-k,t}^b$ . The entries are test statistic will be  $\chi^2(1)$ . *DJC* stands for Dow Jones Cash Market, *DJF* for Dow Jones Futures Market, *SPC* for S&P 500 Cash Market, and *SPF* for S&P 500 Futures Market. All entries are p-values. Whenever an entry is boldfaced, the benchmark model is better than the alternative model, implying that the benchmark model significantly outperforms the alternative model. Normal-faced entries with low p-values mean that the alternative model significantly outperforms the benchmark. The tests involve rolling 5-year samples for estimation and 2-year out-of-sample forecast performances rolling over one month at the time - starting with the 1997-2001 estimation sample.

|            | One-day ahead forecasts      |             |             |             | One-week ahead forecasts |             |             |             | One-month ahead forecasts |             |             |             |
|------------|------------------------------|-------------|-------------|-------------|--------------------------|-------------|-------------|-------------|---------------------------|-------------|-------------|-------------|
|            | <i>DJC</i>                   | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  | <i>DJC</i>               | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  | <i>DJC</i>                | <i>DJF</i>  | <i>SPC</i>  | <i>SPF</i>  |
|            | Evaluation sample: 2001-2006 |             |             |             |                          |             |             |             |                           |             |             |             |
| HAR-RV-J   | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.03</b>              | <b>0.02</b> | <b>0.07</b> | <b>0.02</b> | <b>0.35</b>               | <b>0.33</b> | <b>0.32</b> | <b>0.32</b> |
| HAR-S-RV-J | <b>0.02</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.05</b>              | <b>0.15</b> | <b>0.18</b> | <b>0.08</b> | <b>0.40</b>               | <b>0.38</b> | <b>0.40</b> | <b>0.32</b> |
| SYMM       | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.03</b>              | <b>0.01</b> | <b>0.12</b> | <b>0.02</b> | <b>0.38</b>               | <b>0.31</b> | 0.49        | <b>0.58</b> |
| ASYMLS     | <b>0.00</b>                  | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | <b>0.03</b>              | <b>0.01</b> | <b>0.05</b> | <b>0.03</b> | <b>0.42</b>               | <b>0.31</b> | 0.35        | <b>0.87</b> |
|            | Evaluation sample: 2001-2008 |             |             |             |                          |             |             |             |                           |             |             |             |
| HAR-RV-J   | <b>0.09</b>                  | <b>0.13</b> | <b>0.08</b> | <b>0.17</b> | <b>0.03</b>              | <b>0.06</b> | <b>0.04</b> | <b>0.15</b> | 0.48                      | <b>0.25</b> | <b>0.24</b> | <b>0.35</b> |
| HAR-S-RV-J | <b>0.09</b>                  | <b>0.17</b> | <b>0.09</b> | <b>0.13</b> | <b>0.04</b>              | <b>0.09</b> | <b>0.06</b> | <b>0.16</b> | <b>0.40</b>               | <b>0.30</b> | <b>0.28</b> | <b>0.35</b> |
| SYMM       | <b>0.13</b>                  | <b>0.04</b> | <b>0.07</b> | <b>0.02</b> | <b>0.50</b>              | <b>0.12</b> | <b>0.38</b> | 0.00        | 0.58                      | <b>0.21</b> | 0.36        | <b>0.39</b> |
| ASYMLS     | <b>0.63</b>                  | <b>0.04</b> | <b>0.08</b> | <b>0.07</b> | <b>0.53</b>              | <b>0.15</b> | <b>0.57</b> | <b>0.50</b> | 0.50                      | 0.42        | 0.46        | 0.52        |

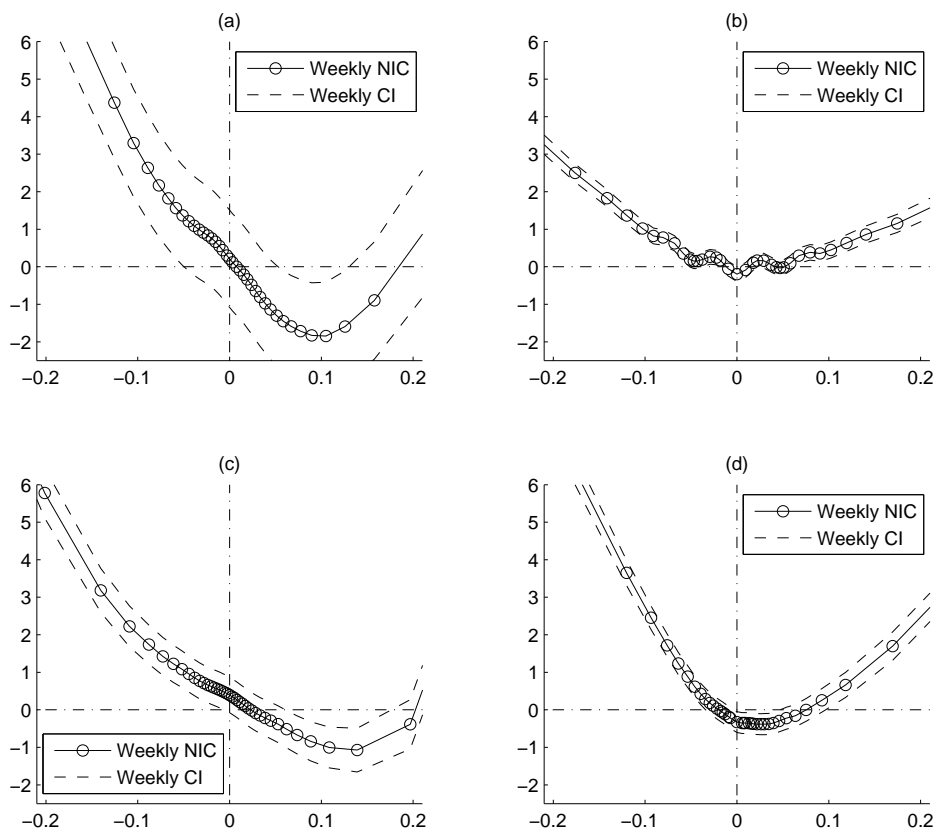
**Figure 1: One-day ahead news impact curves for SP models**

The plots represent estimates of semi-parametric news impact curves - i.e. the function  $NIC$  - as specified in equation (3.1). To facilitate the interpretation and display of results, the news impact is scaled by the mean of  $RV$  for each series/horizon - so that the news impact is in terms of fraction of average horizon volatility. Results for four series using five minute intra-daily returns are displayed. They are: (a) Dow Jones Cash Market; (b) Dow Jones Futures Market; (c) S&P 500 Cash Market; and (d) S&P 500 Futures Market. The confidence bands are computed according to formula (A.15) appearing in the Appendix.



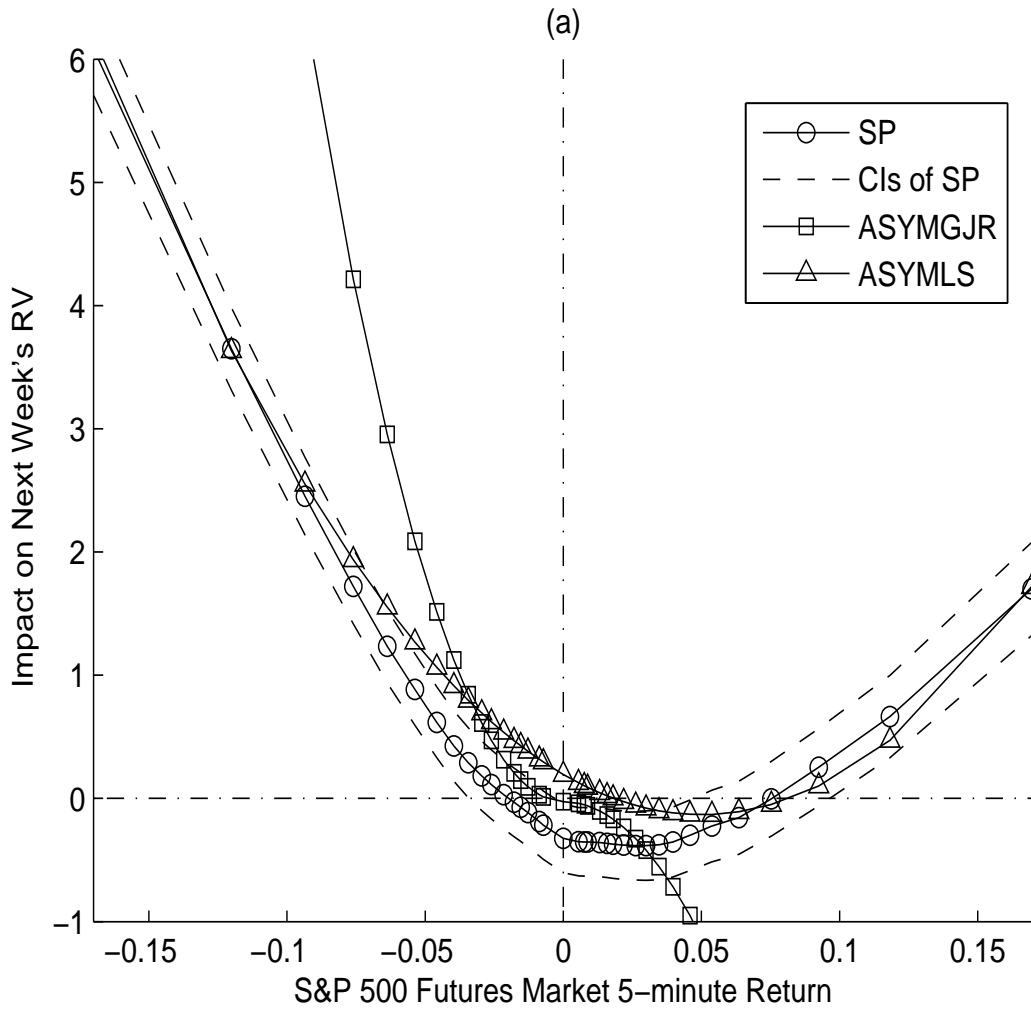
**Figure 2: One-week ahead news impact curves for SP models**

The plots represent estimates of semi-parametric news impact curves - i.e. the function  $NIC$  - as specified in equation (3.1). To facilitate the interpretation and display of results, the news impact is scaled by the mean of  $RV$  for each series/horizon - so that the news impact is in terms of fraction of average horizon volatility. Results for four series using five minute intra-daily returns are displayed. They are: (a) Dow Jones Cash Market; (b) Dow Jones Futures Market; (c) S&P 500 Cash Market; and (d) S&P 500 Futures Market. The confidence bands are computed according to formula (A.15) appearing in the Appendix.



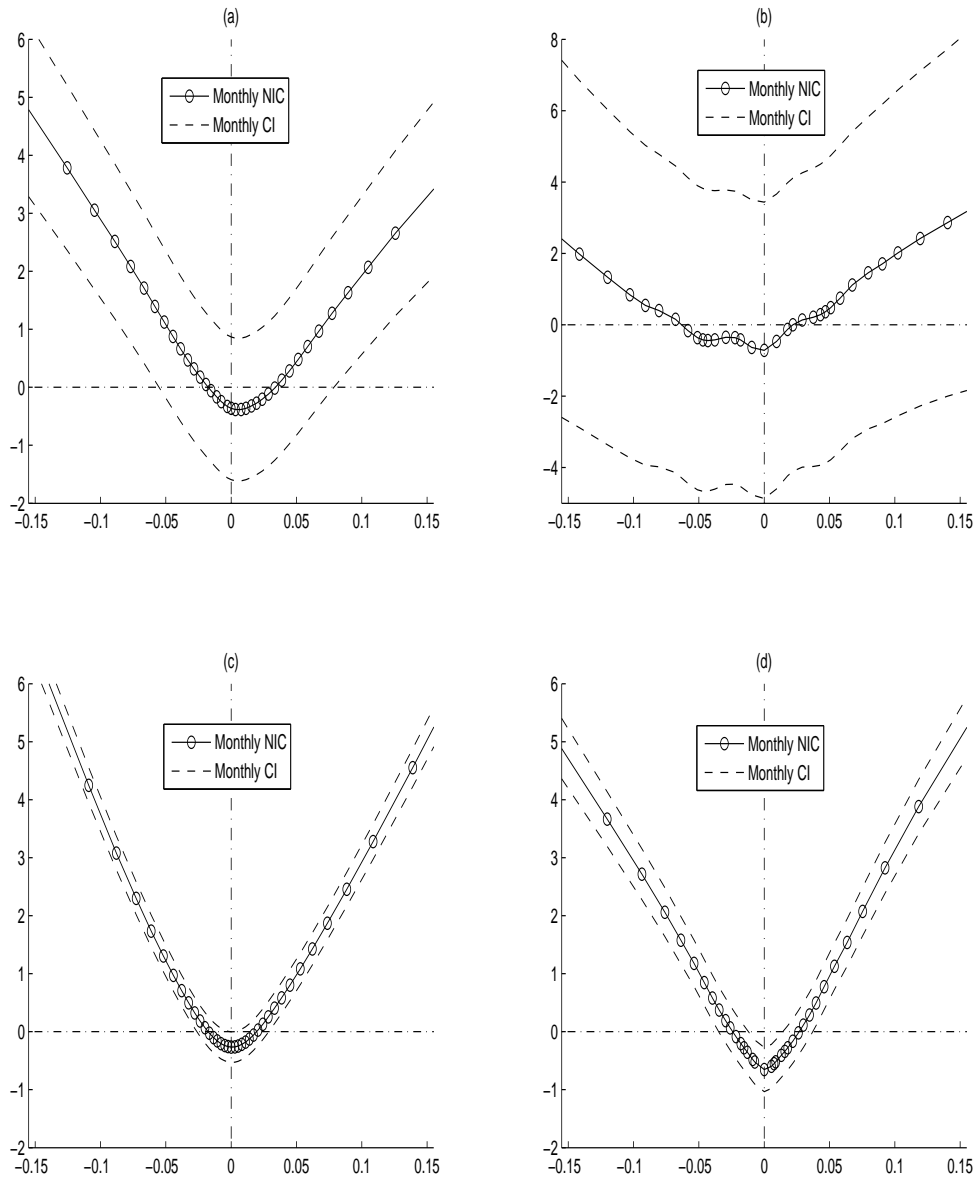
**Figure 3: One-week and one-month ahead news impact curves for semi-parametric and parametric MIDAS models**

The plots represent estimates of semi-parametric and parametric news impact curves for different horizons. The results pertain to the S&P 500 Futures Market. Hence, the SP part is a repeat of plot (b) of Figure 2 and the confidence bands are again computed according to formula (A.15) appearing in the Appendix.



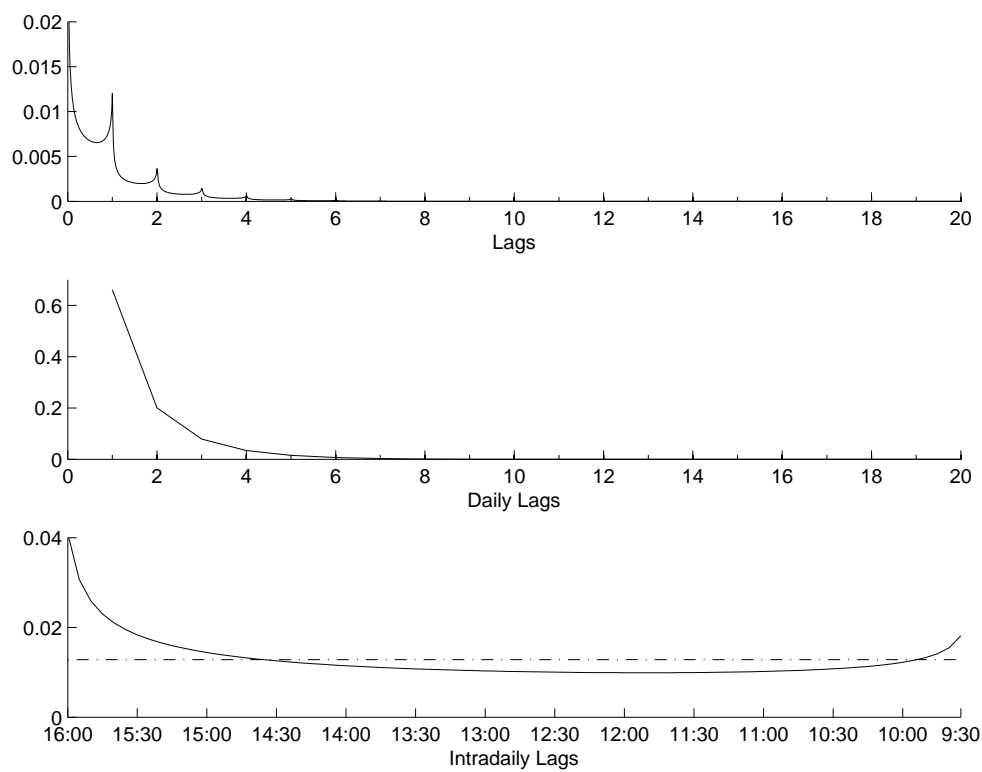
**Figure 4: One-month ahead news impact curves for SP models**

The plots represent estimates of semi-parametric news impact curves - i.e. the function  $NIC$  - as specified in equation (3.1). Results for four series using five minute intra-daily returns are displayed. They are: (a) Dow Jones Cash Market; (b) Dow Jones Futures Market; (c) S&P 500 Cash Market; and (d) S&P 500 Futures Market. The confidence bands are computed according to formula (A.15) appearing in the Appendix.



### Figure 5: Parametric polynomial lag estimates of semi-parametric MIDAS

This figure shows the lag polynomials of the semi-parametric MIDAS regression using the S&P 500 futures data. The first plot provides the product of the daily and intra-daily Beta polynomials appearing in equation (3.2). The second contains only the daily polynomial whereas the third only the intra-daily.



**Figure 6: High frequency returns before and during the 2007-2008 crisis**

The plots represent the 2005-2006 and 2007-2008 samples histograms - throughout the day in different time zones of the trading day - of the 5 minute returns.

