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Macro-Financial Linkages in the High-Frequency Domain: the Effects of Uncertainty on Realized Volatility

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Abstract

This paper estimates a bivariate HEAVY system including daily and intra-daily volatility equations and its macro-augmented asymmetric power extension. It focuses on economic factors that exacerbate stock market volatility and represent major threats to financial stability. In particular, it extends the HEAVY framework with powers, leverage, and macro effects that improve its forecasting accuracy significantly. Higher uncertainty is found to increase the leverage and macro effects from credit and commodity markets on stock market realized volatility. Specifically, Economic Policy Uncertainty is shown to be one of the main drivers of US and UK financial volatility alongside global credit and commodity factors.

Keywords: asymmetries, economic policy uncertainty, HEAVY model, high-frequency data, macro-financial linkages, power transformations, realized variance, risk management.

JEL classification: C22, C58, D80, E44, G01, G15

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1 Introduction

Modelling and forecasting stock market volatility are both of crucial importance to investors for the purposes of derivatives pricing, portfolio immunization, investment diversification, firm valuation, and funding choices. The behaviour of volatility is also closely monitored by policymakers given its potentially destabilizing effects on the financial system. In particular, the global financial crisis of 2007/08 led to a sharp increase in volatility and its persistence (with systemic risk externalities) and thus to a renewed interest in developing an appropriate modelling framework.

This paper addresses this issue by proposing an extension of the HEAVY model of Shephard and Sheppard (2010)[1] which augments the bivariate system with asymmetries and power transformations through the APARCH structure of Ding et al. (1993). The benchmark specification with leverage and power effects has already been shown to improve considerably on Bollerslev's (1986) GARCH model (see, for example, Karanasos and Kim, 2006). The present study provides evidence that the suggested augmented specification outperforms the benchmark one. The optimal estimation of the power term and the asymmetric response to positive and negative shocks embedded in the time-varying volatility pattern have already proved to be one of the most important innovations in the GARCH family of models (see, for example, Brooks et al., 2000). Specifically, Pérez et al. (2009) among others show that the presence of an asymmetric response of volatility to positive and negative returns shows up in non-zero cross-correlations between the original returns and future powers of absolute returns. Our first finding is that each of the two powered conditional variances is significantly affected by the first lags of both power transformed variables, that is, squared negative returns, and realized variance. Second, we extend the asymmetric power specification with macro effects from Economic Policy Uncertainty, bond and commodity market benchmarks, providing a competing framework for volatility modelling to the well-established practice of financial instruments trading and risk measuring based on economic fundamentals. We apply the macro-augmented model to five stock indices and find that realized volatility is significantly affected by the macro variables and their inclusion improves the model's forecasting performance. Finally, we examine not only the direct destabilizing effect of uncertainty on realized volatility (by using it as a regressor), but also the impact on each parameter of the system, and demonstrate that higher uncertainty magnifies the leverage and macro effects from credit and commodity markets.

Our framework contributes to two main strands of the empirical macro-finance literature, namely volatility modelling as well as the investigation of macro-financial linkages and the effects of uncertainty on the stability of financial markets using high-frequency data. We show that the bivariate system including the two volatility equations is suitable not only for stock market returns but also for further asset classes

[1] The acronym HEAVY stands for High-Frequency-Based Volatility (see Shephard and Sheppard, 2010).

or financial instruments (e.g. exchange rate, cryptocurrency, commodity, real estate, and bond returns, choosing in each case appropriate macro proxies besides uncertainty) and multiple applications in financial economics, such as bonds investing, foreign exchange trading and commodities hedging, and core daily functions in the treasuries of most financial and non-financial corporations. Specifically, it outperforms the benchmark specification in terms of both short- and long-term forecasting properties (note that trading and risk management are mostly based on one- to ten-day forecasts while policymakers focus on longer-term predictions of financial volatility). This is shown through a Value-at-Risk example that has both risk management and policy implications.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the extended HEAVY specification, which allows for asymmetries, power transformations, and macro effects. Section 4 describes the data and Section 5 presents the results for the benchmark and the macro-augmented asymmetric power models. Section 6 analyses the forecasting properties of the alternative models by comparing their multiple-step-ahead forecasts. Section 7 focuses on the uncertainty effects on the parameters of the HEAVY specifications. Finally, Section 8 offers some concluding remarks.

2 Literature Review

There is a large body of literature focusing on modelling and forecasting realized volatility. Several studies apply non-parametric estimation methods to high-frequency data. Andersen and Bollerslev (1998), Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002) were the first to use quadratic variation-like measures, while Barndorff-Nielsen et al. (2008, 2009) focused on the realized kernel estimation as a realized measure which is more robust to noise. Various studies combine it with the conditional variance of returns. Engle (2002b) proposed the GARCH-X process, where the former is included as an exogenous variable in the equation of the latter. Corsi et al. (2008) suggested the HAR-GARCH formulation for modelling realized volatility. Hansen et al. (2012) introduced the Realized GARCH model that is closely related to the HEAVY framework of Shephard and Sheppard (2010), which jointly estimates conditional variances using both daily (squared returns) and intra-daily (it uses the realized measure - kernel and variance - as a measure of ex-post volatility) data, so that the system of equations adapts to information arrivals more rapidly than the classic daily GARCH process. One of its advantages is its robustness to structural breaks, especially during crisis periods, since the mean reversion and short-run momentum effects result in higher quality performance in volatility level shifts and more reliable forecasts. Borovkova and Mahakena (2015) employed a HEAVY specification with a skewed-t error distribution, while Huang et al. (2016) incorporated the HAR structure of the realized measure in the GARCH conditional variance specification in order to capture the long memory of the volatility dynamics.

The financial econometrics literature on realized volatility mostly ignores important macro factors that may affect its pattern in the high-frequency domain. It mainly uses lower frequency economic variables (monthly or quarterly). From the seminal studies of Schwert (1989) and Hamilton and Lin (1996), who were among the first to link monthly stock market volatility to the business cycle, till those of Engle and Rangel (2008) and Engle et al. (2013), who applied a mixed frequency approach (Spline- and MIDAS-GARCH), most research has focused on macro factors at a lower than daily frequency to explain the time-varying behaviour of financial volatility. Corradi et al. (2013) investigate the effects of the macroeconomic environment on monthly stock returns, volatilities, and volatility risk-premia, while Conrad and Loch (2015) modelled the S&P 500 daily conditional variance using quarterly economic variables. The main finding of these studies on the determinants of volatility is its counter-cyclical pattern in the case of several economic activity variables.

In the present paper, we examine the role of uncertainty, in addition to other macro proxies, in volatility modelling using the news-based Economic Policy Uncertainty Index, the only uncertainty metric with a daily frequency provided by Baker et al. (2016) for the United States and the United Kingdom and considered as the most comprehensive one, since it includes both economic and policy-related factors giving rise to uncertainty. Exploring the effects of uncertainty effects on financial volatility is very topical in the aftermath of the global financial crisis of 2007-8, since when there has been renewed interest in this 'amorphous' concept (Bloom, 2014). Following the Knightian definition (Knight, 1921) and the early studies on uncertainty by Bernanke (1983) and Dixit and Pindyck (1994), academics and practitioners have attempted to measure this latent variable affecting the decision-making process by economic agents. Consumers' spending and saving behaviour, firms' hiring, financing and investment choices, investors' asset allocation, central banks' and government policy decisions are heavily affected by their 'inability to forecast the likelihood of events happening' according to Knight (Bloom, 2014). There is evidence that uncertainty disrupts the real economy through its effects on financial markets, namely by dampening general confidence and discouraging market participants from doing business. Further, at times of high uncertainty, households tend to reduce consumption and increase precautionary savings and firms postpone investments ('wait and see' tactics) and refrain from hiring. Similarly, stock market investors become more cautious, asset price fall (either through the discount rate or the cash flow channel) and volatility jumps (Pastor and Veronesi, 2013). A higher risk premium increases the cost of capital and generally the financing costs for firms (Alessandri and Mumtaz, 2019) and undermines trust in the financial system.

In what follows, we first review various uncertainty measurement approaches in order to highlight the relative merits of the Economic Policy Uncertainty index and briefly discuss the relevant empirical evidence.

2.1 Uncertainty Measurement Approaches

A variety of methods have been used to measure economic uncertainty including econometric forecasting techniques, text-mining and machine-learning algorithms, survey data, news stories, Google search volumes and Internet-click data. Implied volatility (e.g. the VIX) is widely thought to be a reliable proxy for uncertainty in macro-financial modelling (Bloom, 2009, Bekaert et al., 2013); another traditional approach to gauge uncertainty uses the second moment of the time series of macroeconomic or financial indicators (see, e.g., the GARCH conditional variance in Fountas and Karanasos, 2007). More recently, researchers have developed sophisticated structural models for large-scale macroeconomic and financial datasets (Mumtaz and Theodoridis, 2018, Jurado et al., 2015, Carriero et al., 2018). A further strand of the uncertainty literature has produced survey-based uncertainty measures, using among others the Surveys of Professional Forecasters (Scotti, 2016, Rossi and Sekhposyan, 2015, Jo and Sekkel, 2019).

Baker et al. (2016) were among the first to apply textual analysis to construct an Economic Policy Uncertainty (EPU) Index by calculating the frequency of references to uncertainty concerning economic policy in leading newspapers (counting keywords such as uncertainty and economic policy). Nowadays the EPU Index is computed for many countries (see the indices publicly available on http://www.policyuncertainty.com/) at a monthly frequency (daily EPUs are constructed only for US and UK) and has been extended to obtain several category sub-indices (i.e. uncertainty on fiscal, monetary, trade policy, etc.). The motivation for news-based indicators is the belief that the press is a reliable and a timely mirror of agents' expectations and economic sentiment, since newspapers should cover the economy according to readers' information demand, interests and expectations in order to maintain their audience. Following the seminal paper by Baker et al. (2016) several more have been produced that use textual search and machine learning methods to construct similar news-based Policy Uncertainty indices (Brogaard and Detzel, 2015, Larsen and Thorsrud, 2018). Two related approaches are based on headline counts from news agencies like Bloomberg and Thomson Reuters (see, for example, Caporale et al., 2018) and Internet search engines volume metrics for keywords related to uncertainty or to economic terms, event or variables, indicating that such terms attract the attention of the general public in the presence of uncertainty (Google trends in Castelnuovo and Tran, 2017, Wikipedia searches in Vlastakis and Markellos, 2012, and Bitly click data in Benamar et al., 2018).

2.2 The Economic Policy Uncertainty Index

The key difference between the two main approaches to constructing news-based indices, namely news coverage, and Internet search engines or clicks, lies in their information perspective. The former is based on the information supply side, while the latter on the demand side. We believe that the supply side is more reliable for quantifying uncertainty since newspapers as information providers should reflect the general mood in order to attract and maintain their audience; thus, the media content is of immense value for gauging uncertainty. On the other hand, the demand side, directly connected to economic psychology and measured by Internet queries and news clicks intensity, may generate a biased measure of uncertainty since the clicks volume also depends on people's free time and Internet access, in addition to implying attention or information search as a response to uncertainty. Therefore, in this paper we focus on Economic Policy Uncertainty. The advantages of the EPU index can be summarized as follows: i) the insights derived from real-time news coverage, ii) the timeliness of news arrival with their sound signalling potential, iii) its availability for the main economies, iv) the policy-sensitive feature included in the uncertainty measurement, and v) its explanatory and predictive power in the context of macro-financial models for which there is ample empirical evidence. Given the facts that i) EPU relies on daily news, ii) political news dominates the markets, and iii) the construction of the index includes policy-related concerns in addition to economic factors, we regard it as the most informative index. The model- and survey-based uncertainty proxies cannot be as up-to-date as EPU owing to their reliance on the history of economic variables or non-real-time survey responses by forecasters, whose disagreement or forecast error dispersion do not necessarily suggest the omnipresence of uncertainty in the economy. Newspapers can be thought of as the best illustration of the general public's (households, corporations, investors and governments) feeling in terms of uncertainty, although they are occasionally criticized in relation to their objectivity, on the grounds that they may create news instead of simply transmitting it. In this case, the use of wide-ranging sources to construct the EPU indices eliminates the possibility of one or more newspapers attempting to inflate or conceal ubiquitous uncertainty.

It is important to note here that news textual analysis is used broadly in various scientific fields to quantify societal trends and public opinion. Nowadays, this novel strategy has come to the aid of economic science for measuring variables not directly observable, such as uncertainty, leading to a long list of EPU indices that have gained remarkable popularity in numerous applications in economics and finance. Interestingly, they have recently started showing up even in media reports and investment recommendations. A large literature has developed connecting EPU with macro aggregates, microeconomic data, and financial variables. Most of it investigates the explanatory or the predictive power of EPU for business cycles (with the following variables included: unemployment in Caggiano et al., 2017, output and inflation in Colombo, 2013, Jones and Olson, 2013, Karaman and Yildirim-Karaman, 2019, economic development in Scheffel, 2016, monetary dynamics in Aastveit et al., 2017, Tarassow, 2019, the yield curve slope in Connolly et al., 2018, foreign exchange rates in Kido, 2016, bank credit and bailouts in Bordo et al., 2016, Caliendo et al., 2018, EPU spillovers in Gabauer and Gupta, 2018, Balli et al., 2017, Klößner and Sekkel, 2014), asset prices, returns, volatilities and correlations - equities in Pastor and

Veronesi, 2012, Kelly et al., 2016, Dakhlaoui and Aloui, 2016, bonds in Bernal et al., 2016, stock-bond correlation in Li et al., 2015, commodities in Andreasson et al., 2016, Bakas and Triantafyllou, 2019, real estate in Christou et al., 2017, sovereign credit ratings in Boumparis et al., 2017, CDS spreads in Wisniewski and Lambe, 2015, cryptocurrencies in Fang et al., 2019), and at the micro-level on corporate accounting numbers (Gulen and Ion, 2015, Pham, 2019, Zhong et al., 2019), firm and household decisions (Nagar et al., 2018, Ben-David et al., 2018). Granger causality tests, Structural VARs, Diebold-Yilmaz (DY) dynamic interconnectedness (Diebold and Yilmaz, 2009), Quantile regressions, GARCH models with MIDAS specifications in many cases, when variables of mixed frequencies are involved, and with Dynamic Conditional Correlations (Engle, 2002a), when the dynamic nature of correlations is considered, are among the most common modelling approaches adopted in EPU empirical studies.

However, the literature examining the impact of EPU on the realized volatility dynamics of high-frequency financial variables associated with uncertainty is still limited. A few examples are Pastor and Veronesi (2013), who estimated simple OLS regressions for monthly stock returns, volatilities and correlations (unconditional) including the EPU index, and found a positive sign in the case of correlations and volatilities and a negative one in the case of returns, and Antonakakis et al. (2013), who computed Dynamic Conditional Correlations between EPU, S&P 500 Stock Index returns and implied volatility (VIX) pairwise at a monthly frequency, finding a positive EPU-VIX correlation and a negative EPU-returns one, as expected, since high uncertainty worsens stock market performance and increases its volatility. More recently, Fang et al. (2018) have related daily gold futures volatility with the monthly Global EPU index through the GARCH-MIDAS framework; they provide evidence of a strong positive effect of uncertainty on gold volatility and of its power in forecasting the monthly realized volatility of gold futures. Finally, Cho et al. (2018) highlight the fact that high exchange rate volatility is linked with high EPU, which leads to carry trade losses.

3 The Econometric Framework

The benchmark HEAVY model of Shephard and Sheppard (2010) can be extended in many directions. We allow for power transformations, leverage and macroeconomic effects in the conditional variance process and estimate an augmented version including these three additional features to improve volatility modelling and forecasting.

3.1 The HEAVY Model

The HEAVY model uses two variables: the close-to-close stock returns (r_t) and the realized measure of variation based on high-frequency data, RM_t. We first calculate the signed square rooted (SSR) realized measure as follows: $\widetilde{RM_t} = sign(r_t)\sqrt{RM_t}$, where $sign(r_t) = 1$, if $r_t \geqslant 0$ and $sign(r_t) = -1$, if $r_t < 0$.

We assume that the returns and the SSR realized measure are characterized by the following relations:

$$r_t = e_{rt}\sigma_{rt}, \ \widetilde{RM_t} = e_{Rt}\sigma_{Rt}, \tag{1}$$

where the stochastic term e_{it} is independent and identically distributed $(i.i.d)$, $i = r, R$; σ_{it} is positive with probability one for all t and it is a measurable function of $\mathcal{F}_{t-1}^{(XF)}$, that is the filtration generated by all available information through time $t-1$. We will use $\mathcal{F}_{t-1}^{(HF)}$ $(X = H)$ for the high-frequency past data, i.e., for the case of the realized measure, or $\mathcal{F}_{t-1}^{(LoF)}$ $(X = Lo)$ for the low-frequency past data, i.e., for the case of the close-to-close returns. Hereafter, for notational convenience, we will drop the superscript XF.

In the HEAVY/GARCH model e_{it} has zero mean and unit variance. Therefore, the two series have zero conditional means, and their conditional variances are given by

$$\mathbb{E}(r_t^2 \,|\mathcal{F}_{t-1}) = \sigma_{rt}^2, \text{ and } \mathbb{E}(\widetilde{RM_t}^2 \,|\mathcal{F}_{t-1}) = \mathbb{E}(RM_t \,|\mathcal{F}_{t-1}) = \sigma_{Rt}^2, \tag{2}$$

where $\mathbb{E}(\cdot)$ denotes the expectation operator. The returns equation is called HEAVY-r and, similarly, the realized measure equation is denoted as HEAVY-R.

3.2 The Macro-augmented Asymmetric Power Specification

The asymmetric power (AP) specification for the HEAVY$(1,1)$ model consists of the following equations (in what follows, for notational simplicity, we drop the order of the model if it is $(1,1)$):

$$(1-\beta_i L)(\sigma_{it}^2)^{\frac{\delta_i}{2}} = \omega_i + (\alpha_{ir} + \gamma_{ir}s_{t-1})L(r_t^2)^{\frac{\delta_r}{2}} + (\alpha_{iR} + \gamma_{iR}s_{t-1})L(RM_t)^{\frac{\delta_R}{2}}, \tag{3}$$

where L is the lag operator, $\delta_i \in \mathbb{R}_{>0}$ (the set of the positive real numbers), for $i = r, R$, are the power parameters, and $s_t = 0.5[1 - sign(r_t)]$, that is, $s_t = 1$ if $r_t < 0$ and 0 otherwise; γ_{ii}, γ_{ij} $(i \neq j)$ are the own and cross leverage parameters, respectively[2]; positive γ_{ii}, γ_{ij} means a larger contribution of negative 'shocks' in the volatility process. In this specification the powered conditional variance, $(\sigma_{it}^2)^{\delta_i/2}$, is a linear function of the lagged values of the powered transformed squared returns and realized measure.

We will distinguish between three different asymmetric cases: the double one (DA: $\gamma_{ij} \neq 0$ for all i and j) and two more, own asymmetry (OA: $\gamma_{ij} = 0$ for $i \neq j$ only) and cross asymmetry (CA: $\gamma_{ii} = 0$).

The α_{iR} and γ_{iR} are called the (four) Heavy parameters (own when $i = R$ and cross when $i \neq R$). These parameters capture the impact of the realized measure on the two conditional variances. Similarly, the α_{ir} and γ_{ir} (four in total) are called the Arch parameters (own when $i = r$ and cross for $i \neq r$). They capture the influence of the squared returns on the two conditional variances.

[2] This type of asymmetry was introduced by Glosten et. al. (1993).

The asymmetric power model is equivalent to a bivariate AP-GARCH process for the returns and the SSR realized measure (see, for example, Conrad and Karanasos, 2010). If all four Arch parameters are zero, then we have the AP version of the benchmark HEAVY specification, where the only unconditional regressor is the first lag of the powered RM_t.

Next, we provide a comparison between the benchmark HEAVY system and the more general AP specification. Their difference is captured by the matrix $\mathbf{C}$ (see eq. (B.6) of the Supplementary Appendix). We will examine the bivariate case, which is when $N = 2$. For the more general DAP specification, $\mathbf{C}$ is a full matrix with: i) diagonal elements given by $\beta_i + (\alpha_{ii} + \gamma_{ii}/2)z_i$, $i = r, R$, where $z_i = \mathbb{E}(|e_{it}|^{\delta_i}$, and ii) off-diagonal elements given by $(\alpha_{ij} + \gamma_{ij})z_j$, $i, j = r, R$, for $i \neq j$. For the benchmark model, since $\gamma_{ij} = 0$, $z_i = 1$, for all $i, j = r, R$, and $\alpha_{Rr} = 0$, $\mathbf{C}$ is restricted to being an upper diagonal matrix. That is, we have

$$\text{DAP Specification:} \qquad \mathbf{C}= \begin{bmatrix} \beta_r + (\alpha_{rr} + \gamma_{rr}/2)z_r & (\alpha_{rR} + \gamma_{rR}/2)z_R \\ (\alpha_{Rr} + \gamma_{Rr}/2)z_r & \beta_R + (\alpha_{RR} + \gamma_{RR}/2)z_R \end{bmatrix}$$

$$\text{Benchmark HEAVY} \quad : \qquad \mathbf{C}= \begin{bmatrix} \beta_r & \alpha_{rR} \\ 0 & \beta_R + \alpha_{RR} \end{bmatrix}.$$

Figure 1 presents the comparison of the benchmark and DAP-HEAVY models' forecasting performance (see also Section 6). We apply the optimal predictor $|\mathbf{r}_t|^{\wedge\boldsymbol{\delta}}$ (under Proposition 3 of the Supplementary Appendix) on S&P 500 returns and realized variance data and calculate 50-step ahead forecasts. The more general specification produces forecasts significantly closer to the actual values for both returns (Fig.1, a & b) and realized measure (Fig.1, c & d). Most importantly, its forecasts of the peaks of returns and realized variance are more accurate. The benchmark model is outperformed by our proposed asymmetric power extension in predicting low- and high-frequency volatility indicators. It produces, mostly, lower volatility forecasts (dotted lines) in comparison with the DAP (dashed lines) and actual (solid lines) values. Therefore, our main contribution, that is the asymmetric power extension, provides a significant improvement on the HEAVY system of Shephard and Sheppard (2010).

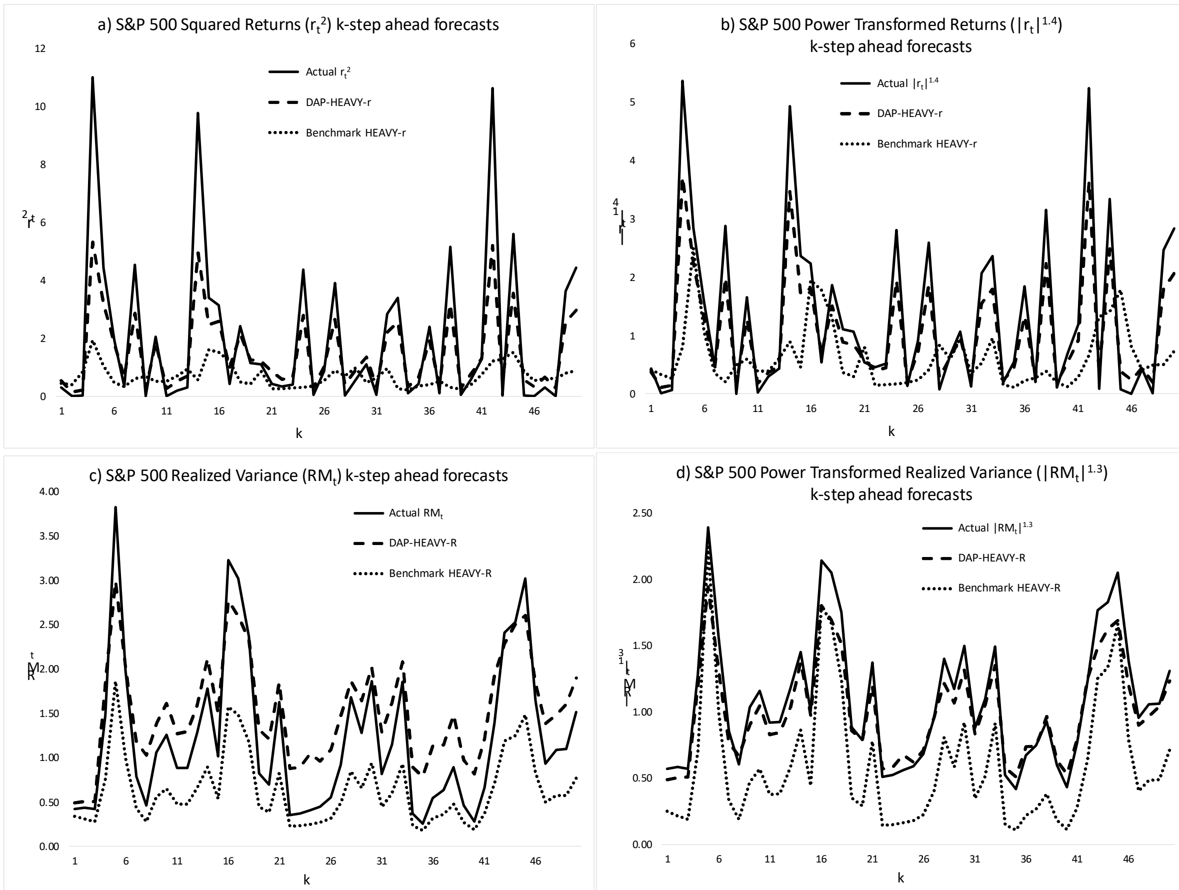

Figure 1. S&P 500 Returns and Realized Variance k-step ahead forecasts

Furthermore, we should mention that all the parameters in this bivariate system should take non-negative values (see, for example, Conrad and Karanasos, 2010). We extend the realized measure equation with the non-negative macro proxies: the Economic Policy Uncertainty, EPU_t, the Bonds (the Merrill Lynch MOVE treasury bonds implied volatility index or the Moody's AAA corporate bonds yields), BO_t, and the Commodities (the S&P GSCI index or the Crude oil WTI prices), CO_t, market benchmark indices. The macro-augmented (m) AP-HEAVY system is characterized by the following equation for the realized measure:

$$\begin{aligned}(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} &= \omega_i + (\alpha_{Rr}+\gamma_{Rr}s_{t-1})L(r_t^2)^{\frac{\delta_r}{2}} + (\alpha_{RR}+\gamma_{RR}s_{t-1})L(RM_t)^{\frac{\delta_R}{2}} \\ &\quad +\phi_R EPU_{t-1} + \zeta_R BO_{t-1} + \vartheta_R CO_{t-1}.\end{aligned} \tag{4}$$

Eq. (4) incorporates three Macro parameters, ϕ_R, ζ_R, and ϑ_R, which capture the macro effects on the power transformed realized measure. The returns equation remains the same as in the non-augmented specification without the direct effect from the macro variables ($\phi_r, \zeta_r, \vartheta_r = 0$).

To sum up, the benchmark model (eq. (2)) is characterized by two conditional variance equations, the GARCH(1,0)-X formulation for returns and the GARCH(1,1) formulation for the SSR realized measure:

$$\text{HEAVY-}r\text{: } (1 - \beta_r L)\sigma^2_{rt} = \omega_r + \alpha_{rR} L(RM_t),$$
$$\text{HEAVY-}R\text{: } (1 - \beta_R L)\sigma^2_{Rt} = \omega_R + \alpha_{RR} L(RM_t).$$

Eq. (4) gives the general formulation of our macro-augmented extension for RM_t, which adds asymmetries and power transformations to the benchmark specification (see also the Supplementary Appendix for the relevant theoretical considerations). We also use the existing Gaussian quasi-maximum likelihood estimators (QMLE) and multistep-ahead predictors already applied (Ding et al., 1993) in the APARCH framework (see, for example, He and Teräsvirta 1999, Laurent, 2004, Karanasos and Kim, 2006). We will first estimate both conditional variance equations in the general form with all the Heavy, Arch, and Asymmetry parameters given by eq. (4) and whenever a parameter is insignificant, we will exclude it and this will result in a reduced form that is statistically preferred for each volatility process. For example, in the returns and realized measure conditional variances estimation, the own and cross Arch parameters (α_{rr} and α_{Rr} respectively) prove to be insignificant and, are therefore, excluded (see Section 5, Table 3, Panels A and B) to obtain our preferred specification for both returns and realized measures.

4 Data Description

The HEAVY framework is estimated for five stock indices returns and realized volatilities. According to the analysis in Shephard and Sheppard (2010), this formulation considerably improves volatility modelling by allowing momentum and mean reversion effects and adjusting quickly to the structural breaks in volatility. As already mentioned, we extend the benchmark specification in Shephard and Sheppard (2010), by adding the features of power transformed conditional variances, leverage, and macro effects in the volatility process. Moreover, in order to identify the possible recent global financial crisis effects on the volatility process and to take into account the structural breaks in the two powered series (squared returns and realized measure), we incorporate dummies in our empirical investigation (the results are available in the Supplementary Appendix).

4.1 Oxford-Man Institute's Library

We use daily data for four US and one UK stock market indices extracted from the Oxford-Man Institute's (OMI) realized library version 0.3 (Heber et al., 2009): S&P 500 (SP), Dow Jones Industrial Average

(DJ), Nasdaq 100 (NASDAQ) and Russell 2000 (RUSSELL) from the US and FTSE 100 (FTSE) from the UK. Our sample covers the period from 03/01/2000 to 01/03/2019 for most indices. For the UK index, the data start in 2001. The OMI's realized library includes daily stock market returns and several realized volatility measures calculated on high-frequency data from the Reuters DataScope Tick History database. The data are first cleaned and then used in the realized measures calculations. According to the library's documentation, the data cleaning consists of deleting records outside the time interval during which the stock exchange is open. Some minor manual changes are also needed when the results are ineligible due to the re-basing of indices. We use the daily closing prices, P_t^C, to form the daily returns as follows: $r_t = [\ln(P_t^C) - \ln(P_{t-1}^C)] \times 100$, and two realized measures as drawn from the library: the 5-minute realized variance and the realized kernel. The estimation results using the two alternative measures are very similar, so we present only the ones with the realized variance (the results for the realized kernel are available upon request).

4.2 Realized Measures

The library's realized measures are calculated in the way described in Shephard and Sheppard (2010). The realized kernel, which we use as an alternative to the realized variance (these results are not reported but are available upon request), is calculated using a Parzen weight function as follows: $RK_t = \sum_{k=-H}^{H} k(h/(H+1))\gamma_h$, where $k(x)$ is the Parzen kernel function with $\gamma_h = \sum_{j=|h|+1}^{n} x_{j,t}x_{j-|h|,t}$; $x_{jt} = X_{t_{j,t}} - X_{t_{j-1,t}}$ are the 5-minute intra-daily returns where $X_{t_{j,t}}$ are the intra-daily log-prices and $t_{j,t}$ are the times of trades on the t-th day. Shephard and Sheppard (2010) declared that they selected the bandwidth of H as in Barndorff-Nielsen et al. (2009).

The 5-minute realized variance, RV_t, which we choose to present here, is calculated with the formula: $RV_t = \sum x_{j,t}^2$. Heber et al. (2009) additionally implement a subsampling procedure from the data to the most feasible level in order to eliminate the stock market noise effects. The subsampling involves averaging across many realized variance estimations from different data subsets (see also the references in Shephard and Sheppard, 2010 for realized measures surveys, noise effects and subsampling procedures).

Table 1 presents the five stock indices extracted from the database and provides volatility estimates for each all squared returns and realized variances time series over the corresponding sample period (see also the stock index series graphs in Appendix A.2, Figures A.1 - A.10). We calculate the standard deviation of the series and the annualized volatility, where the latter is the square rooted mean of 252 times the squared return or the realized variance. The standard deviations are always lower than the annualized volatilities. The realized variances have lower annualized volatilities and standard deviations than the squared returns since they ignore the overnight effects and are affected by less noise. The returns represent the close-to-close yield and the realized variances the open-to-close variation. The annualized volatility of the realized measure is between 14% and 18%, while the squared returns show figures from 18% to 25%.

Table 1: Data Description

	Total Sample period			r_t^2		RV_t	
Index	Start date	End date	Obs.	Avol	sd	Avol	sd
SP	03/01/2000	01/03/2019	4809	0.190	0.046	0.165	0.024
DJ	03/01/2000	01/03/2019	4804	0.179	0.040	0.166	0.026
NASDAQ	03/01/2000	01/03/2019	4803	0.250	0.070	0.176	0.022
RUSSELL	03/01/2000	01/03/2019	4803	0.238	0.059	0.136	0.015
FTSE	02/01/2001	01/03/2019	4581	0.182	0.039	0.172	0.028

Notes: Avol is the annualized volatility and sd is the standard deviation.

Next, we examine the sample autocorrelations of the power transformed absolute returns $|r_t|^{\delta_r}$ and signed square rooted realized variance $|SSR\_RM_t|^{\delta_R}$ for various values of δ_i. Figures 2 and 3 show the autocorrelograms of the S&P 500 index from lag 1 to 120 for $\delta_r = 1.4, 1.7, 2.0$ and $\delta_R = 1.3, 1.6, 2.0$ (similar autocorrelograms for the other four indices are available upon request). The sample autocorrelations for $|r_t|^{1.4}$ are greater than those of $|r_t|^{\delta_r}$ for $\delta_r = 1.7, 2.0$ at every lag up to at least 120 lags. In other words, the most interesting finding from the autocorrelogram is that $|r_t|^{\delta_r}$ has the strongest and slowest decaying autocorrelation when $\delta_r = 1.4$. Similarly, for the realized measure, the power with the strongest autocorrelation function is $\delta_R = 1.3$. Furthermore, Figures 4 and 5 present the sample autocorrelations of $|r_t|^{\delta_r}$ and $|SSR\_RM_t|^{\delta_R}$ as a function of δ_i for lags $1, 12, 36, 72$ and 96. For example, for lag 12, the highest autocorrelation values of power transformed absolute returns and signed square rooted realized variance are calculated closer to the power of 1.5 and 1.0, respectively. These figures provide our motivation for extending the Benchmark HEAVY through the APARCH framework of Ding et al. (1993) and confirm the power choice of our econometric models, which is $\delta_r = 1.4$ for returns and $\delta_R = 1.3$ for the realized measure (see Section 5).

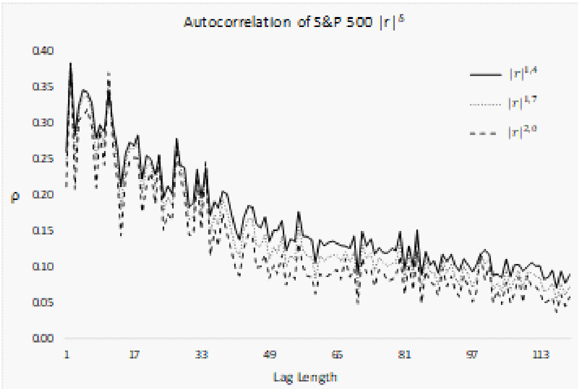

Figure 2. Autocorrelation of S&P 500 $|r_t|^{\delta_r}$ for $\delta_r = 1.4, 1.7, 2.0$

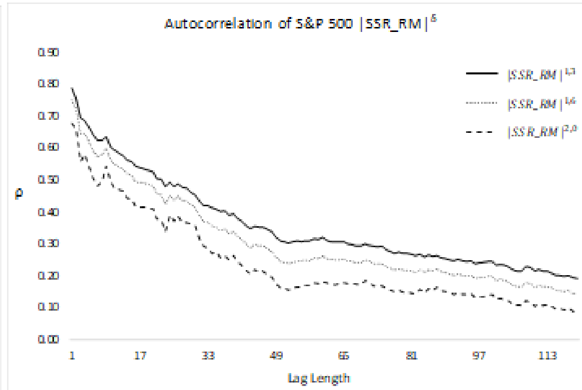

Figure 3. Autocorrelation of S&P 500 $|SSR\_RM_t|^{\delta_R}$ for $\delta_R = 1.3, 1.6, 2.0$

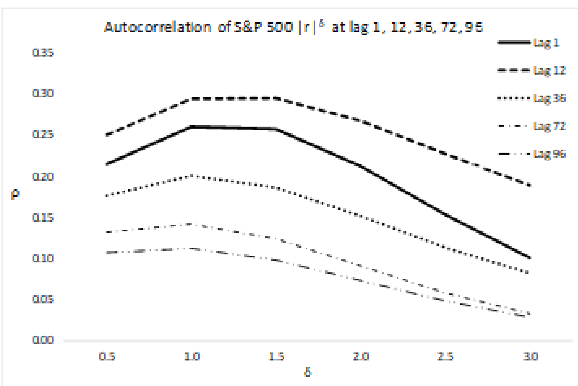

Figure 4. Autocorrelation of S&P 500 $|r_t|^{\delta_r}$ at lags $1, 12, 36, 72, 96$

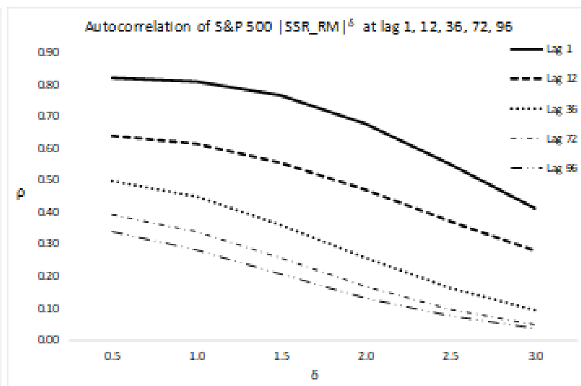

Figure 5. Autocorrelation of S&P 500 $|SSR\_RM_t|^{\delta_R}$ at lags $1, 12, 36, 72, 96$

4.3 Macroeconomic Proxies

In order to shed light on macro-financial linkages, we augment the financial volatility HEAVY process with non-negative macro proxies at the daily frequency. Motivated by a gap in the literature, we augment the model for both daily and intra-daily volatility with daily macro variables that proxy the business cycle conditions used in the existing monthly or quarterly studies of volatility determinants. In line with Conrad and Loch (2015), we proxy the macroeconomic environment through economic activity, monetary and business conditions, and sentiment daily variables that could explain stock index realized variance. Since GDP, industrial production, unemployment, inflation, consumer sentiment or any available activity, monetary base, and sentiment index are not measured on a daily basis, we turn to relevant daily variables. The Economic Policy Uncertainty index is directly related to the business cycle with significant contractionary effects on investment and employment (Baker et al., 2016). It is used here in place of the activity variables included in all prior studies. We expect the opposite sign to economic activity variables since uncertainty is negatively correlated to activity and higher uncertainty is strongly associated with recessions. The uncertainty index applied is also considered as an alternative to financial uncertainty (VIX index in Corradi et al., 2013), sentiment, and macroeconomic volatility (Conrad and Loch, 2015). Daily credit condition variables are chosen to account for the impact of business and monetary conditions on financial volatility, following Schwert (1989), who uses financial leverage variables, interest rate and corporate bond returns volatility. Lastly, we use daily commodity price indices because commodity price increases and oil, in particular, are often associated with macroeconomic recessions (Barsky and Kilian, 2004). Therefore, we expect a significant surge in stock market volatility following a rise in commodity prices, which has been proved to be harmful for real economic activity.

Our first macro variable is the news-based Economic Policy Uncertainty Index, created by Baker et al. (2016) and retrieved from http://www.policyuncertainty.com/. The site, maintained by Baker, Bloom, and Davis, provides daily EPU data for two countries, the US and the UK, starting from 1985 and 2001, respectively. This is the reason why we use the OMI library data for FTSE modelling from 2001 instead of 2000 as in the case of the US indices. The EPU index effectively captures the broad 'amorphous' concept of economic uncertainty (Bloom, 2014). Its advantages relative to other uncertainty measures have already been discussed (see Section 2).

Concerning credit market conditions, we use two alternative Bond market global benchmarks: the Merrill Lynch MOVE 1 month Index (MOVE) and the Moody's AAA Corporate Bonds Yields (M.AAA). The MOVE Index is an estimate of the Option Implied Volatility of US Treasury bonds. It is the Treasury counterpart of the 'fear' index (VIX) for the S&P 500 and captures the sovereign credit market stance. Higher sovereign bond volatility denotes higher turbulence in the credit channel for sovereigns with direct spillovers to financial and non-financial corporations' credit conditions. The Moody's index provides daily averages of global triple-A corporate bond yields (higher yields denote higher cost of financing for corporations) and is used as an alternative to the MOVE index for the credit channel. Moreover, the Commodities market conditions are proxied by two alternative global factors: the S&P GSCI Index (GSCI) and the Crude Oil Prices per barrel (WTI). Both capture the cost of production for firms in the economy, where rising commodity values can lead to production and investment deterioration due to increased cost effects on economic activity. The S&P Goldman Sachs Commodity Index is the most widely-recognized commodity markets performance benchmark. The crude oil is the most important commodity as an energy source across all economies. The crude oil dollar prices per barrel (crude stream: West Texas Intermediate - WTI) are used as our alternative macro regressor to the GSCI, where, besides oil, most liquid commodities are incorporated. The four bonds and commodities variables are retrieved from Thomson Reuters Datastream and FRED economic database of the St. Louis Federal Reserve Bank.

All daily macro regressors are log-transformed (see graphs in Appendix A.2, Figures A.11 - A.16) and included in the realized measure equation where they are shown to be jointly significant[3]. In the macro-augmentation of the HEAVY model, we are restricted to using only non-negative variables with estimated positive coefficients due to the GARCH positivity constraints. Consequently, we focus our analysis of the macro-financial linkages on the EPU index for uncertainty and the four bonds and commodities variables, which are characterized by non-negative values only and have a magnifying impact on realized volatility. Increased uncertainty, bond yields, and volatility and commodity prices, all contribute to financial volatility heightening, especially during economic downturns. Figures 6-9 clearly show that higher realized volatility is observed in times of high uncertainty, credit market turbulence and commodity prices boost.

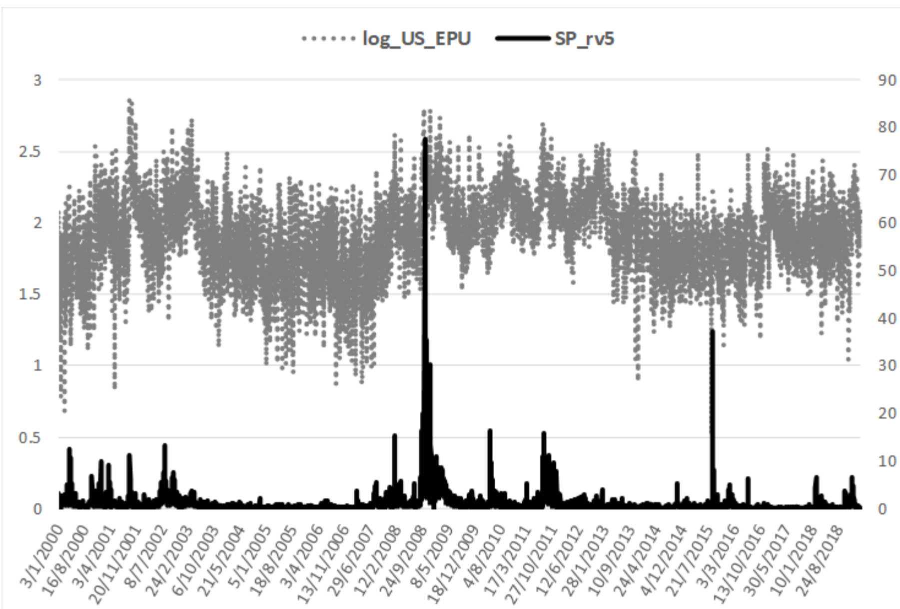

Figure 6. US EPU and S&P 500 Realized Variance

[3]The log-transformed series are always positive because all series' values are higher than one. Since the lower bound of our macro regressors' series is not one but zero, we, alternatively, included the regressors divided by 100 (EPU, MOVE, WTI), 10000 (GSCI) and 10 (M.AAA). This resulted in similar estimated coefficients in terms of level and significance within the HEAVY framework (results available upon request).

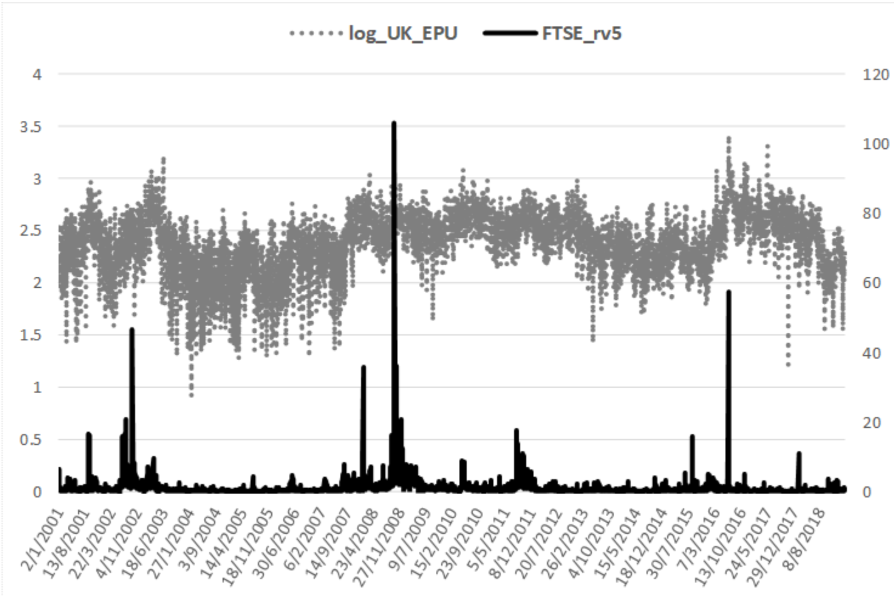

Figure 7. UK EPU and FTSE 100 Realized Variance

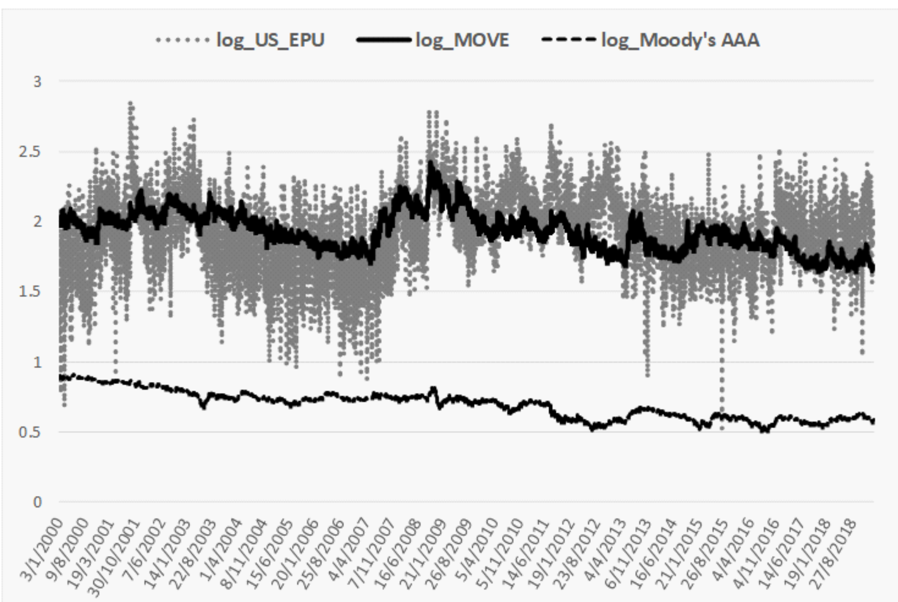

Figure 8. US EPU and the Credit market proxies

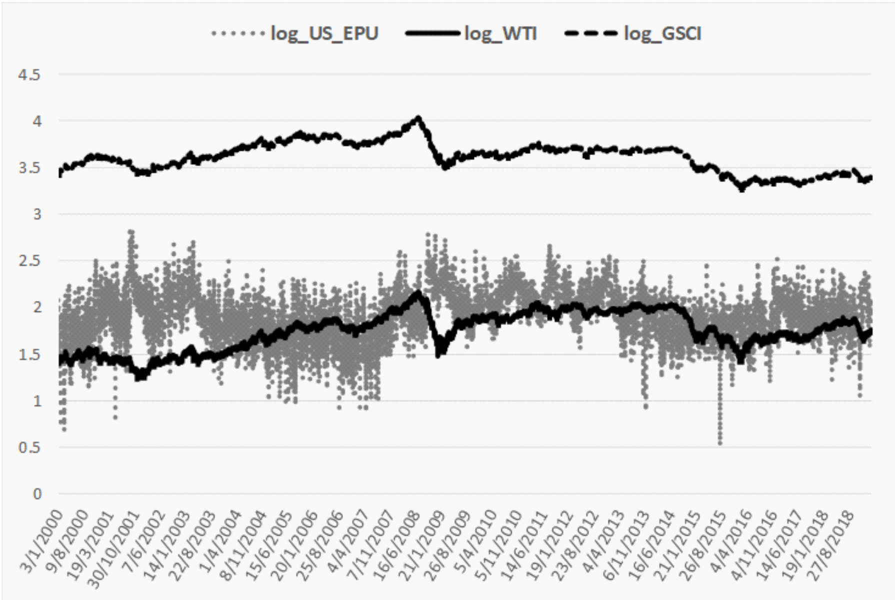

Figure 9. US EPU and the Commodity market proxies

In addition to imposing the GARCH constraints, we initially tested a non-negative proxy of the real estate market (the log-transformed Dow Jones [DJ] REIT index). This proved to be highly significant but should be excluded from the model because the negative sign of the relevant coefficient violates our econometric framework constraints[4]. A better performance of the real estate sector is associated with a higher REIT's level mostly in economic growth periods and is negatively related to financial volatility. Finally, the realized variance is affected negatively by two economic activity indicators with values not constrained to be positive and thus also excluded. We used the Aruoba-Diebold-Scotti (ADS) Business Conditions Index (Aruoba et al., 2009) and the Yield Curve slope, which are some of the very few economic activity indicators available on a daily frequency. The ADS index tracks daily real business conditions based on economic data releases and the Yield Curve slope, calculated as the difference between the 10-year and the 3-month Treasury bond yields, has been shown to be a powerful predictor of future economic activity (Estrella and Hardouvelis, 1991). As expected, financial volatility is affected negatively by both variables, since lower ADS and term structure slope values indicate an economic worsening associated with higher stock market volatility. This opens several paths for future research on macro-financial linkages in the high-frequency domain to connect these three variables (DJ REIT, ADS, Yield Curve slope), excluded here, with realized variation measures in the absence of positivity constraints within the econometric framework applied.

[4] Further research could consider an exponential HEAVY specification to address the non-negativity limitations.

5 Estimation Results

Following the introduction of the GARCH-X specification of Engle (2002b) that included realized measures as exogenous regressors in the conditional variance equation, Han and Kristensen (2014) and Han (2015) studied its asymptotic properties with a fractionally integrated (nonstationary) process included as covariate (see also Francq and Thieu, 2019). Nakatani and Teräsvirta (2009) and Pedersen (2017) focused on the multivariate case, the so-called extended constant conditional correlation, which allows for volatility spillovers, and they developed inference and testing for the QMLE parameters (see also Ling and McAleer, 2003, for the asymptotic theory of vector ARMA-GARCH processes). For the extended HEAVY models, we employ the existing Gaussian QMLE and multistep- ahead predictors applied in the APARCH framework (see, for example, He and Teräsvirta, 1999, Laurent, 2004, Karanasos and Kim, 2006). Following Pedersen and Rahbek (2019), we first test for ARCH effects and after rejecting the conditional homoscedasticity hypothesis we apply one-sided significance tests of the covariates added to the estimated GARCH processes.

We first estimate the benchmark formulation as in Shephard and Sheppard (2010), that is, without asymmetries, power transformations, and macro effects, obtaining very similar results (Table 2). For this specification the only unconditional regressor in both equations is the first lag of the RM_t. In other words, the chosen returns equation is a GARCH$(1,0)$-X process leaving out the own Arch effect, α_{rr}, from lagged squared returns since it becomes insignificant when we add the cross-effect of the lagged realized measure as a regressor, with a Heavy coefficient, α_{rR}, high in value and significant for all indices. The momentum parameter, β_r, is estimated to be around 0.63 to 0.70. For the SSR realized variance, the best model is the GARCH$(1,1)$ without the cross-effect from lagged squared returns. The Heavy term, α_{RR}, is estimated between 0.37 and 0.54 and the momentum, β_R, is around 0.44 to 0.62. The benchmark HEAVY system of equations chosen (with three alternative GARCH models being tested for each dependent variable with order: $(1,1)$, $(1,0)$-X, and the most general one, that is, $(1,1)$-X) is the same as in Shephard and Sheppard (2010), with similar parameter values and the same conclusion that the realized measure of variation is the key determinant of the conditional variances of stock returns and the SSR realized variance. However, this does not hold for the more richly parametrized macro-augmented asymmetric power model. In particular, according to the Sign Bias test (SBT) of Engle and Ng (1993), the asymmetric effect is omitted from the benchmark specification with the sign coefficient always significant (p-values lower than 0.11).

Table 2: The Benchmark HEAVY model.

	SP	DJ	NASDAQ	RUSSELL	FTSE
Panel A. Stock Returns: HEAVY- r					
$(1-\beta_r L)\sigma^2_{rt} = \omega_r + \alpha_{rR} L(RM_t)$					
β_r	**0.63** (12.56)***	0.66 (15.77)***	0.65 (12.36)***	<u>0.70</u> (18.92)***	0.64 (14.08)***
α_{rR}	0.48 (6.83)***	0.39 (7.38)***	0.65 (6.30)***	<u>0.71</u> (7.65)***	**0.38** (7.22)***
Q_{12}	16.72 [0.08]	15.19 [0.23]	15.43 [0.22]	13.69 [0.19]	4.65 [0.97]
SBT	2.46 [0.01]	1.60 [0.11]	1.59 [0.11]	1.87 [0.06]	2.57 [0.01]
lnL	−6364.15	−6180.79	−7611.05	−7998.95	−6067.59
Panel B. Realized Measure: HEAVY- R					
$(1-\beta_R L)\sigma^2_{Rt} = \omega_R + \alpha_{RR} L(RM_t)$					
β_R	0.52 (13.52)***	0.57 (13.64)***	**0.44** (13.20)***	0.54 (14.92)***	<u>0.62</u> (15.99)***
α_{RR}	0.48 (10.99)***	0.44 (9.00)***	<u>0.54</u> (14.96)***	0.42 (12.34)***	**0.37** (8.96)***
Q_{12}	12.64 [0.40]	11.85 [0.46]	7.87 [0.80]	19.97 [0.07]	10.23 [0.60]
SBT	4.64 [0.00]	3.70 [0.00]	2.47 [0.01]	3.13 [0.00]	2.68 [0.01]
lnL	−5691.96	−5798.58	−6040.92	−5093.92	−5858.93

Notes: The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.05, 0.10, 0.15 level, respectively. Bold (underlined) numbers indicate minimum (maximum) values across the five indices. Q_{12} is the Box-Pierce Q-statistics on the standardized residuals with 12 lags. SBT denotes the Sign Bias test of Engle and Ng (1993). lnL denotes the log-likelihood value for each specification. The numbers in square brackets are p-values.

Table 3 presents the estimation results for the chosen macro-augmented asymmetric power specifications. Wald and t-tests are carried out to test the significance of the Heavy and Arch parameters, and they reject the null hypothesis at the 10% level in all cases. Since all the parameters take non-negative values, we use one-sided tests (see, for example, Pedersen and Rahbek, 2019).

For both returns and realized variance, the selected model is the double asymmetric power (DAP) one since both power transformed conditional variances are significantly affected by own and cross asymmetries. We estimate the power terms separately with a two-stage procedure, as follows: first, we estimate univariate asymmetric power specifications for the returns and the realized measure; the Wald tests for the estimated power terms (available upon request) reject the hypotheses of $\delta_i = 1$ and $\delta_i = 2$ in most cases. In the second stage, we use the estimated powers, δ_r and δ_R, from the first step to power transform the conditional variances of both series and incorporate them into the bivariate model. The sequential procedure produces the fixed power term values, which are the same for both specifications (δ_r and δ_R are common for Panels A and B).

For the returns (see Panel A), the estimated power, δ_r, is either 1.40 or 1.50. The Heavy cross-effect and asymmetry parameters, α_{rR} and γ_{rR}, are highly significant in most cases, apart from the Russell index returns, for which the Heavy cross-effect, α_{rR}, is insignificant and not included. Although α_{rr} is insignificant and excluded in all cases, the own asymmetry parameter (γ_{rr}) is significant with $\gamma_{rr} \in [0.04, 0.11]$. In other words, the lagged values of both powered variables, that is, the realized measure and the squared negative returns, drive the model of the power transformed conditional variance of the returns. Moreover, the momentum parameter, β_r, is estimated to be around 0.76 to 0.91. All five indices generated very similar DAP specifications without macro effects since our realized measure equation includes the macro variables.

Similarly, for the realized measure the preferred specification is the m-DAP one. The estimated power, δ_R, is 1.30 in all cases and consistently lower than the returns power term (see Panel B). Both Heavy parameters, α_{RR} and γ_{RR}, are significant: α_{RR} is around 0.13 (min. value) to 0.32 (max. value), while the own asymmetry, γ_{RR}, is between 0.03 and 0.07. Moreover, the cross asymmetry Arch parameter is always significant with $\gamma_{Rr} \in [0.04, 0.10]$. This means that the power transformed conditional variance of $\widetilde{RM}_t$ is significantly affected by the lagged values of both powered variables: squared negative returns and realized measure. Further, the momentum parameter, β_R, is estimated to be around 0.55 to 0.77.

Lastly, the lagged macro effects are highly significant, with the expected positive sign in all cases (see Panel B). The power transformed realized variance receives a boosting impact from higher EPU levels, $\phi_R \in [0.01, 0.02]$, in line with the results of Pastor and Veronesi (2013), who were the first to associate stock market volatilities with EPU, and results in a positive link. The uncertainty effect also confirms the finding of Conrad and Loch (2015), among others, on the negative effect of consumer confidence (University of Michigan Consumer Sentiment Index), which is the opposite sentiment to uncertainty and is estimated here with the expected opposite sign as well. For the US indices, we use the daily US EPU index, and for FTSE 100, the UK EPU instead. Regarding the bond and commodity markets, we prefer to use common global proxies for both the US and UK stock markets. Bond market conditions are better captured by the MOVE index in all cases except for Nasdaq 100, where we prefer the Moody's triple-A yields. As expected, increased US treasury implied volatility or higher quality international corporate bond yields increase realized volatility in stock markets ($\zeta_R \in [0.03, 0.14]$), since the turbulence in the credit markets always generates significant volatility spillover effects to stock markets. This is consistent with the study of Engle and Rangel (2008), who estimate a positive effect of short-term government bond interest rate volatility on stock market volatility through the Spline-GARCH specification. Turning to commodities, the realized measure equation of Nasdaq 100 does not include a significant commodities proxy, while for S&P 500 and Dow Jones, we prefer the GSCI index ($\vartheta_R = 0.03$) and for Russell 2000 and FTSE 100, the WTI crude oil prices ($\vartheta_R \in [0.01, 0.05]$) are the chosen commodity regressors. Lower commodity prices mean decreased cost of supplies for firms in the economy, which boosts productivity, investment and, more generally, economic growth and, at the same time, reduces stock market volatilities. Given that higher oil prices mostly coincide with recession periods (Barsky and Kilian, 2004), the positive link between realized variance and commodity prices, captured by ϑ_R, supports the negative association of economic activity with stock market volatility, in accordance with the existing literature. All prior studies on the determinants of volatility have provided clear evidence of the negative effect of economic activity proxies on stock market volatility (see, for example, the GDP growth coefficients in Engle and Rangel, 2008).

Overall, our results show strong Heavy effects (captured by the α_{rR}, γ_{rR}, α_{RR}, and γ_{RR} parameters), as well as asymmetric Arch influences (the estimated γ_{rr} and γ_{Rr} are always significant) and macro impact (measured by ϕ_R, ζ_R and ϑ_R). The log-likelihood (lnL) values are always higher for the m-DAP specifications compared to the benchmark one, that is the one without asymmetries, powers, and macro effects, proving the superiority of our model's in-sample estimation (see also the comparison of the two models in terms of the S&P 500 standardized residuals graphs in Appendix A.2, Figure A.17). The SBT statistics further show that the asymmetric effect is not omitted anymore since the sign coefficients are insignificant, with p-values consistently higher than 0.14. Table A.1 (in Appendix A.1) provides additional results for the realized measure equation step-by-step estimation, firstly, with the DAP extension (Panel A), and, secondly, the m-DAP with the EPU regressor only (Panel B). We followed the particular stepwise estimation procedure before producing our final chosen model extending the HEAVY-R with powers, asymmetries and all three macro factors.

From an economic point of view, the macro effects on stock market volatility observed through the m-DAP framework confirm prior studies suggesting an upward volatility trajectory during economic downturns. This counter-cyclical behaviour has been mainly shown by the negative effect of economic activity leading or coincident indicators with a monthly or quarterly frequency (Engle and Rangel, 2008). Turning to the high-frequency domain for macro-financial linkages, the monthly activity variables should be replaced by possible daily proxies of economic activity to be included as explanatory variables in the realized variance equation. Given the non-negativity restriction, we could not use, among others, the daily term spread, a reliable predictor of GDP (Estrella and Hardouvelis, 1991) and significant in the monthly context as evidenced by Conrad and Loch (2015). Based on the rich empirical evidence of the adverse uncertainty effects on economic activity (Caggiano et al. 2017, Colombo, 2013, Jones and Olson, 2013), we select the daily EPU index to associate stock market volatility with a variable directly linked to economic activity. The positive sign consistently estimated across all specifications for the EPU variable is in accordance with prior findings on the positive effect of macroeconomic uncertainty (Schwert, 1989) and unemployment, and the negative effect of real GDP, industrial production, and consumer sentiment growth (Conrad and Loch, 2015).

We also selected the sovereign bond yield volatility (or, alternately, the corporate bond yield level) to identify the credit channel effect on stock markets. Increased volatility in the sovereign bond market (Engle and Rangel, 2008) or corporate debt yields are correlated with macroeconomic turbulence since they increase the cost of financing for firms and investors and, consequently, reduce activity. Accordingly, the global bond factor coefficients are consistently estimated with positive signs across all stock market volatility models (see also Asgharian et al., 2013). Finally, the commodity price index or, alternatively, the oil price are included as a third volatility determinant, which is found to be positive and highly significant in most cases. Given the evidence on effects of commodity prices on the macroeconomy (see, for example, Barsky and Kilian, 2004), we also include them and find a destabilizing impact of higher daily commodity prices, mostly associated with economic downturns, on stock market realized variance. Higher commodity prices increase production costs for firms as well as the volatility of equities. Hence, in addition to contributing to the literature on realized variance modelling through the asymmetric, power, and macro-augmentation of the benchmark HEAVY specification, we also shed light on the economic sources of volatility by exploring the macro-financial linkages in the high-frequency domain with daily macro proxies. All three daily economic variables that exacerbate stock market volatility (higher economic uncertainty, tighter credit conditions, and increased commodity prices) are associated with weak economic conditions. Moreover, we bridge the macro-finance literature with the high-frequency volatility studies by using, for the first time, the only economic uncertainty index computed daily.

Table 3: The m-DAP-HEAVY model.

	SP	DJ	NASDAQ	RUSSELL	FTSE
			Panel A. Stock Returns: m-DAP-HEAVY- r		
			$(1-\beta_r L)(\sigma_{rt}^2)^{\frac{\delta_r}{2}} = \omega_r + \gamma_{rr} s_{t-1} L(r_t^2)^{\frac{\delta_r}{2}}$ $+(\alpha_{rR} + \gamma_{rR} s_{t-1}) L(RM_t)^{\frac{\delta_R}{2}}$		
β_r	**0.76** (27.79)***	0.79 (35.15)***	**0.76** (21.26)***	<u>0.91</u> (79.69)***	0.82 (33.49)***
α_{rR}	0.13 (4.33)***	0.09 (4.02)***	<u>0.24</u> (4.34)***		**0.06** (2.74)***
γ_{rr}	**0.04** (2.20)***	0.08 (4.16)***	0.05 (2.78)***	<u>0.11</u> (10.23)***	<u>0.11</u> (6.93)***
γ_{rR}	<u>0.18</u> (5.95)***	0.12 (4.87)***	<u>0.18</u> (4.50)***	**0.05** (2.58)***	0.09 (3.92)***
Q_{12}	12.19 [0.27]	15.61 [0.21]	14.00 [0.30]	13.47 [0.20]	6.21 [0.91]
SBT	1.38 [0.17]	0.88 [0.38]	0.16 [0.87]	0.75 [0.46]	1.32 [0.19]
lnL	−6268.35	−6135.97	−7586.31	−7897.30	−5741.93
			Panel B. Realized Measure: m-DAP-HEAVY- R		
			$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{RR} + \gamma_{RR} s_{t-1}) L(RM_t)^{\frac{\delta_R}{2}}$ $+\gamma_{Rr} s_{t-1} L(r_t^2)^{\frac{\delta_r}{2}} + \phi_R EPU_{t-1} + \zeta_R BO_{t-1} + \vartheta_R CO_{t-1}$		
β_R	0.65 (27.72)***	0.69 (32.19)***	**0.55** (22.88)***	0.62 (24.52)***	<u>0.77</u> (35.27)***
α_{RR}	0.21 (10.19)***	0.18 (9.85)***	<u>0.32</u> (15.24)***	0.23 (11.23)***	**0.13** (5.71)***
γ_{RR}	<u>0.07</u> (6.11)***	<u>0.07</u> (5.47)***	**0.03** (2.74)***	<u>0.07</u> (5.55)***	0.04 (2.96)***
γ_{Rr}	0.09 (9.67)***	<u>0.10</u> (8.33)***	0.07 (11.84)***	**0.04** (8.65)***	0.09 (10.95)***
ϕ_R	<u>0.02</u> (3.74)***	<u>0.02</u> (2.57)***	<u>0.02</u> (3.10)***	**0.01** (2.12)***	<u>0.02</u> (3.41)***
ζ_R	0.06 (4.26)*** $MOVE$	0.05 (4.30)*** $MOVE$	<u>0.14</u> (6.34)*** $M.AAA$	**0.03** (2.45)*** $MOVE$	0.06 (4.85)*** $MOVE$
ϑ_R	0.03 (4.41)*** $GSCI$	0.03 (3.90)*** $GSCI$		<u>0.05</u> (6.38)*** WTI	**0.01** (2.19)*** WTI
Q_{12}	15.50 [0.22]	12.83 [0.38]	7.79 [0.80]	19.93 [0.07]	10.82 [0.54]
SBT	1.49 [0.14]	0.63 [0.53]	0.11 [0.91]	1.33 [0.18]	1.08 [0.28]
lnL	−5654.89	−5704.97	−5915.03	−5070.49	−5844.36
			Panel C. Powers δ_i		
δ_r	**1.40**	**1.40**	<u>1.50</u>	**1.40**	<u>1.50</u>
δ_R	**1.30**	**1.30**	**1.30**	**1.30**	**1.30**

Notes: See Notes in Table 2.

Next, we investigate the impact of structural changes (detected in the two power transformed time series used as dependent variables) on the Heavy, Arch and Macro estimated parameters. By carrying out the break tests of Bai and Perron (1998, 2003a,b), we identify three breaks for each volatility series, one for the recent financial crisis of 2007/08, one before and one after the crisis. Therefore, we incorporate structural break slope dummies in the m-DAP specification in order to study the time-varying behaviour of the parameters. When focusing on the recent global financial crisis, we observe that the Heavy, Arch, and Macro parameters consistently increase during the crisis, when the macro effects destabilizing the stock markets are magnified, while in the pre-and post-crisis periods the parameters are lower (these results are included in the Supplementary Appendix).

Lastly, we estimated the bivariate system with the various conditional correlation models: the CCC-Constant Conditional Correlations (Bollerslev, 1990), the DCC-Dynamic Conditional Correlations (Engle, 2002a), the ADCC-Asymmetric Dynamic Conditional Correlations (Cappiello et al., 2006) and the DECO-Dynamic Equicorrelations (Engle and Kelly, 2012). All correlation models produce estimates of the average conditional correlations for the two volatility measures around 0.85. The conditional correlations extension provides identical results for the conditional variance equations (since it is a two-step approach), similar correlation estimates for all indices, and, most importantly, does not improve further the m-DAP-HEAVY specification (see also the Supplementary Appendix). Therefore, we do not report these results (which are available upon request).

6 Forecasting Performance

Following the estimation of the m-DAP extension to the HEAVY framework of equations, we perform multistep-ahead out-of-sample forecasting in order to compare the forecasting accuracy of the enriched specification proposed in this study with the benchmark model introduced by Shephard and Sheppard (2010). We re-estimate the benchmark model, the DAP and its macro-augmented extension for a shortened sample, which spans for SP from 3/1/2000 up to 4/10/2018 (4,709 observations: in-sample estimation) and keep the remaining 100 observations from 5/10/2018 to 1/3/2019 for out-of-sample comparison purposes. With the shortened sample, for each specification we estimate the 100-step-ahead forecasted (power transformed) conditional variances and calculate two standard measures of forecasting performance, that is the Mean Square Error (MSE) and the QLIKE loss function (Patton, 2011). MSE and QLIKE are computed on the basis of the comparison of the forecasted variances to the out-of-sample actuals up to 1/3/2019, for multiple time intervals to observe the forecasting performance across different time horizons (1-, 5-, 10-, 20-, and 100-day-ahead intervals). We follow both static and dynamic forecasting procedures, considering the actual values (static) or the forecasted values (dynamic) beyond the

1-day horizon (actual values are always used for the macro regressors).

The results, presented in Tables 4 and 5 for the SP index (similar forecasting results for the other four indices are available upon request), clearly show that our macro-augmented asymmetric power extensions outperform the benchmark models across all time horizons. For the returns equations (see Panels A, Tables 4-5), the m-DAP formulation dominates the alternative benchmark HEAVY-r with the lowest MSE and QLIKE in all forecasting periods. Static and dynamic forecasts give similar results for returns. Therefore, we report the MSE and QLIKE values of the static forecasts. In the realized measure equation (see Panels B and C, Tables 4-5), we obtain the best 1- and 5-step-ahead forecasting performance from both static and dynamic procedures in the m-DAP specification with the EPU regressor only without Bonds and Commodities. For the 10- and 100-day period ahead, we prefer the m-DAP model with all three macro effects using either static or dynamic forecasts. Finally, for the 1-month forecasts, the static procedure gives lower forecast error in the macro-augmented model with EPU, Bonds, and Commodities, while the dynamic case prefers the macro-extension with EPU only.

Overall, the more general specification proposed in our study performs significantly better than the benchmark one over both the short- and the long-term horizons. When considering the stepwise estimation of the final m-DAP model, we find evidence for, firstly, the significant improvement in forecasting results with the double asymmetric power over the benchmark specification, and, secondly, its further enhancement with macro effects.

Table 4: Mean Square Error (MSE) of m-step ahead forecasts for SP as a Ratio of the benchmark model.

Specifications↓ m-steps →	1	5	10	20	100
Panel A: Stock Returns, static forecasts (HEAVY-r)					
Benchmark	1.000	1.000	1.000	1.000	1.000
m-DAP	**0.054**	**0.998**	**0.986**	**0.961**	**0.945**
Panel B: Realized Measure, static forecasts (HEAVY-R)					
Benchmark	1.000	1.000	1.000	1.000	1.000
DAP	0.709	0.759	0.805	0.808	0.829
m-DAP with EPU	**0.639**	**0.754**	0.803	0.804	0.826
m-DAP with EPU, Bonds & Commodities	0.784	0.777	**0.770**	**0.772**	**0.802**
Panel C: Realized Measure, dynamic forecasts (HEAVY-R)					
Benchmark	1.000	1.000	1.000	1.000	1.000
DAP	0.709	0.659	0.568	0.432	0.342
m-DAP with EPU	**0.639**	**0.651**	0.563	**0.429**	0.342
m-DAP with EPU, Bonds & Commodities	0.784	0.661	**0.562**	0.433	**0.332**

Notes: Bold numbers indicate minimum values across the different specifications.

Table 5: QLIKE Loss Function of m-step ahead forecasts

for SP as a Ratio of the benchmark model.

Specifications↓ m-steps →	1	5	10	20	100
Panel A: Stock Returns, static forecasts (HEAVY-r)					
Benchmark	1.000	1.000	1.000	1.000	1.000
m-DAP	**0.071**	**0.967**	**0.946**	**0.935**	**0.915**
Panel B: Realized Measure, static forecasts (HEAVY-R)					
Benchmark	1.000	1.000	1.000	1.000	1.000
DAP	0.826	0.913	0.939	0.946	0.976
m-DAP with EPU	**0.789**	**0.907**	0.935	0.944	0.974
m-DAP with EPU, Bonds & Commodities	0.868	0.960	**0.921**	**0.932**	**0.948**
Panel C: Realized Measure, dynamic forecasts (HEAVY-R)					
Benchmark	1.000	1.000	1.000	1.000	1.000
DAP	0.826	0.474	0.411	0.388	0.573
m-DAP with EPU	**0.789**	**0.464**	0.404	**0.384**	0.570
m-DAP with EPU, Bonds & Commodities	0.868	0.498	**0.400**	0.412	**0.482**

Notes: Bold numbers indicate minimum values across the different specifications.

The forecasting performance of the proposed models can be further examined in a real-world risk management empirical example. Value-at-Risk (VaR) is a daily metric for market risk measurement, defined as the potential loss in the value of a portfolio, over a pre-defined holding period, for a given confidence level. The most important input in the VaR calculation is the one-day volatility forecast of the risk factor relevant to the trading portfolio under scope. We directly apply our conditional variance forecasts in a long portfolio position to one S&P 500 index contract starting from 4/10/2018. We calculate 100 daily VaR values from 5/10/2018 to 1/3/2019 using the one-day conditional variance forecasts of each model for returns and realized measure (6 models in total). Given that the conditional mean return is zero and the returns follow the normal distribution, first we calculate the one-day VaR with 99% and 95% confidence level. According to the parametric approach to VaR calculations, we multiply the daily portfolio value with the one-day-ahead conditional volatility forecast (equal to the square root of the conditional variance forecast) and the left quantile at the respective confidence level of the normal distribution (the z-scores for 99% and 95% confidence level are 2.326 and 1.645, respectively). Secondly, we calculate the daily realized return of the portfolio (gains and losses) and, thirdly, we perform the backtesting exercise, comparing the realized returns with the respective one-day VaR for the 99% and

95% confidence levels. In the cases where the realized loss exceeds the respective day's VaR value, we record it as an exception in the backtesting procedure, meaning that the VaR metric fails to cover the loss of the specific day's portfolio value.

According to the backtesting results (Table 6: Backtesting results), the number of exceptions across all models is in line with the selected confidence level (the 99% and 95% confidence levels allow for 1 and 5 exceptions, respectively, every 100 days) and low enough to prevent supervisors from increasing the capital charges (in which case we refer to a bank's trading portfolio). The higher number of exceptions means higher market risk capital requirements for financial institutions since regulators heavily penalize banks' internal models that fail to cover trading losses through the VaR estimates. Following the Basel traffic light approach, the market risk capital charge increases when the backtesting exceptions are more than 4 in a sample of 250 daily observations and 99% confidence level. Since all models provide adequate coverage of the realized losses, we should further compare the average and minimum VaR estimates calculated based on the forecasts of each specification (Table 6: Descriptive statistics). The VaR estimate that provides the highest loss coverage with the lowest capital charges is the one with the lowest minimum and highest mean values. This is achieved by the realized measure specifications, for which we prefer the asymmetric power models, augmented or not with the uncertainty proxy. Given that the market risk capital requirement is calculated on the trading portfolio total 99% VaR (absolute value, 60-day average) adjusted by the penalty of the backtesting exceptions (higher than 4 in the 250-day sample), the bank needs the smallest possible VaR average with the larger minimum estimate in absolute terms. Our proposed models clearly satisfy both criteria, contributing to the risk manager's VaR calculation of the volatility forecasts that better capture the loss distribution (highest extreme loss coverage with highest absolute minimum value) without inflating the capital charges (lowest absolute mean).

Table 6: VaR Backtesting results and Descriptive statistics for the SP portfolio.

	Backtesting results		Descriptive statistics			
	No. of Exceptions		99% VaR		95% VaR	
Specifications	99% VaR	95% VaR	Mean	Min.	Mean	Min.
Panel A: Stock Returns (HEAVY-r)						
Benchmark	1	3	-70.46	-129.70	-49.82	-91.71
m-DAP	1	3	-65.19	-119.16	-46.47	-84.25
Panel B: Realized Measure (HEAVY-R)						
Benchmark	1	3	-63.89	-96.74	-45.17	-68.40
DAP	1	3	$\mathbf{-65.11}$	$\mathbf{-107.50}$	-46.03	-76.01
m-DAP with EPU	1	3	$\mathbf{-65.24}$	$\mathbf{-107.87}$	-46.13	-76.27
m-DAP with EPU, Bonds & Commodities	1	3	-56.33	-101.54	-39.83	-71.29

Notes: Mean and Min. denote the average and minimum VaR estimate, respectively. Bold numbers indicate the preferred specifications for the lower market risk capital charge with the higher loss coverage.

Furthermore, the volatility forecasts produced by the m-DAP-HEAVY model are directly applicable to a wide range of business finance operations, alongside the well-established risk management practice outlined in the VaR empirical exercise. Portfolio managers should rely on the proposed framework to predict future volatility in asset allocation and minimum-variance portfolio selection complying with their clients' risk appetite. Risk averse investors' mandates specify low volatility boundaries on their portfolio positions, while risk lovers allow for higher volatilities on the risk-return trade-off of their investments. Accurate volatility predictions can also be used in a forward-looking performance evaluation context, through the risk-adjusted metrics, i.e. the Sharpe or the Treynor risk-adjusted return ratios. Traders and risk managers focus on the volatility trajectory in derivatives pricing, volatility targeting strategies and macro-informed trading decisions. Trading and hedging in financial markets depend on risk factors whose predicted volatilities are the main input of any pricing function applied. Moreover, financial chiefs consider volatility forecasts when they decide on investment projects or funding choices (bond and equity valuation defining the cost of capital) given that expected future cash-flow variation is a critical factor in business analytics.

Finally, policymakers and authorities supervising and regulating the financial system should rely on accurate volatility forecasts in designing macro- and micro-prudential policy responses. The risk management of the financial system is structured as follows: i) identification of risk sources (both endogenous - financial market volatility - and exogenous - the macroeconomy), ii) assessment of the nature of risk factors, iii) risk measurement (micro-prudential metrics at the financial institution level and macro-prudential metrics at the system and markets level), and iv) risk mitigation with proactive regulation and crisis preparedness plans and strategies. Therefore, regulators should employ the macro-informed financial volatility forecasts of the m-DAP-HEAVY model across the whole risk management process and the financial stability oversight tools, such as the early warning systems, the macro stress tests on financial institutions and the bank capital and risk frameworks. For example, the macro stress test scenario inputs, which include, among others, stock market volatility predictions for the financial institutions' trading books, should consider macro-informed volatility estimates to account for the macro effects on financial markets. Economic uncertainty has been shown to play a decisive role across equity markets. Accordingly, it is essential for the Supervisory Authorities to add the uncertainty factor to the regulatory stress tests. Furthermore, complying with the capital and risk frameworks set by supervisors (Basel committee and central banks), financial institutions measure their trading portfolio's market risk (beyond the credit risk of their loan portfolio) with the daily Value-at-Risk (VaR) metric. Given that reliable macro-informed volatility forecasts, provided by our superior modelling framework, improve the VaR estimates considerably, supervisors should encourage banks to improve their market risk internal models with more accurate macro-informed volatility forecasts.

7 The Uncertainty Effect on Realized Volatility

Following the augmentation of the benchmark HEAVY system with asymmetries, power transformations, and macroeconomic effects, we investigate the influence of uncertainty on financial volatility. Over the decade following the global turmoil that created new interest in the role of uncertainty, the most widely used metrics or proxies have all been based on macroeconomic, financial and policy uncertainty, which have been found to have a detrimental impact on the economy and financial markets, which is stage-contingent (with more dampening effects in shakier times). The present study fills a notable gap in the extant EPU literature by documenting its role within our proposed extended HEAVY volatility modelling framework. Our analysis differs from earlier ones in the use of the daily EPU index as a determinant of daily realized volatility, with major implications for macro-informed trading in financial markets and the actions of policymakers overseeing financial stability and managing systemic risk.

We have already highlighted the direct positive effect, in line with Pastor and Veronesi (2013), and forecasting power of daily EPU on realized volatility within the m-DAP framework in Sections 5 and 6 (see also Appendix A.1, Table A.2, the benchmark equation for the realized measure with macro effects for all five stock indices). In this Section, we extend our empirical analysis by focusing more specifically on the main macro determinant of volatility in the realized measure equation, that is the significant EPU effect on the realized variance.

We first investigate the EPU effect in the context of the benchmark realized volatility equation enriched with the lagged bonds' and commodities' variables (these results are available in the Supplementary Appendix) and then within the DAP extension (see also Appendix A.1, Table A.3, with our preferred specifications MOVE and GSCI for the realized measure equation of SP according to AIC). The m-DAP-HEAVY-R equation is estimated using eight restricted forms alternatively to examine each EPU effect separately with the following four interaction terms: i) γ_{RR}^{epu} is the parameter of the lagged EPU multiplied by the lagged realized variance asymmetries, capturing the EPU effect on the own Heavy asymmetry coefficient (γ_{RR}), ii) γ_{Rr}^{epu} measures the EPU effect on the cross Arch asymmetry, iii) ζ_{R}^{epu} and iv) ϑ_{R}^{epu} capture the EPU effect on the bonds' and commodities' proxies, respectively. Table 7 reports the alternative restricted forms for SP with bonds, commodities and four interaction terms of EPU with the two asymmetric Heavy and Arch coefficients and the other two macro parameters (similar results for the other four indices are available upon request). The interaction terms are all positive, which implies an amplifying EPU impact on each parameter. The own Heavy and cross Arch asymmetries are significantly and positively affected by higher uncertainty. Consistently with the macro-augmented benchmark model (Supplementary Appendix, Table F.1), the macro effects are also magnified significantly by higher uncertainty levels. Within the uncertainty literature, the link between credit conditions tightening and uncertainty has recently been investigated by Alessandri and Mumtaz (2019), who associate the rising financing costs for firms with credit market uncertainty, while the commodities-uncertainty relation is widely explored by Antonakakis et al. (2014), Aloui et al. (2016) and Fang et al. (2018) among others. In particular, Antonakakis et al. (2017) focus on the oil prices-stock market volatility link. However, all these studies did not cover the EPU, credit and commodities macro effects on intra-daily financial volatility and the EPU amplifying role through the credit and production cost channels.

Table 7: The m-DAP-HEAVY-R equation for SP with the EPU effect on Heavy, Arch and Macro parameters.

$$(1-\beta_R L)(\sigma^2_{Rt})^{\frac{\delta_R}{2}} = \omega_R + [\alpha_{RR} + (\gamma_{RR} + \gamma^{epu}_{RR} EPU_{t-1}) s_{t-1}] L(RM_t)^{\frac{\delta_R}{2}} +$$
$$(\gamma_{Rr} + \gamma^{epu}_{Rr} EPU_{t-1}) s_{t-1} L(r^2_t)^{\frac{\delta_r}{2}} + (\zeta_R + \zeta^{epu}_R EPU_{t-1}) BO_{t-1} +$$
$$(\vartheta_R + \vartheta^{epu}_R EPU_{t-1}) CO_{t-1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_R	0.64 (27.81)***	0.64 (26.96)***	0.64 (27.03)***	0.65 (27.47)***	0.65 (28.08)***	0.65 (27.66)***	0.66 (29.14)***	0.65 (27.69)***
α_{RR}	0.22 (10.76)***	0.22 (10.80)***	0.22 (10.82)***	0.14 (5.14)***	0.22 (10.93)***	0.21 (10.17)***	0.22 (10.51)***	0.21 (10.19)***
γ_{RR}				0.07 (6.23)***	0.07 (5.88)***	0.07 (6.12)***	0.07 (5.87)***	0.07 (6.11)***
γ^{epu}_{RR}	0.04 (5.92)***	0.04 (5.66)***	0.04 (5.66)***	0.04 (3.53)***				
γ_{Rr}				0.09 (9.56)***	0.09 (9.49)***	0.09 (9.68)***	0.09 (9.59)***	0.09 (9.68)***
γ^{epu}_{Rr}	0.05 (9.32)***	0.05 (9.34)***	0.05 (9.35)***					
ζ_R	0.06 (4.53)*** *MOVE*	0.05 (3.63)*** *MOVE*	0.06 (4.48)*** *MOVE*	0.06 (4.51)*** *MOVE*	0.06 (4.19)*** *MOVE*	0.03 (2.36)*** *MOVE*		0.06 (4.26)*** *MOVE*
ζ^{epu}_R		0.01 (1.54)* *MOVE*			0.01 (2.84)*** *MOVE*	0.01 (3.79)*** *MOVE*		
ϑ_R	0.03 (3.79)*** *GSCI*	0.03 (4.10)*** *GSCI*	0.02 (4.46)*** *GSCI*	0.03 (4.07)*** *GSCI*		0.03 (4.43)*** *GSCI*	0.03 (4.23)*** *GSCI*	0.02 (2.79)*** *GSCI*
ϑ^{epu}_R			0.003 (1.61)* *GSCI*				0.01 (3.95)*** *GSCI*	0.01 (3.80)*** *GSCI*
δ_r				1.40				
δ_R				1.30				

Notes: See notes in Table 2. Superscripts indicate the EPU effect on the respective parameter.

To sum up, our main contribution to the EPU literature consists of the new empirical evidence we provide on the positive link between EPU and realized volatility. Within the HEAVY framework, we firstly prove the EPU destabilizing impact on stock markets with financial volatility investigated with daily frequency. Secondly, we show that the leverage and Heavy effects on the realized variance are state-dependent, being affected by structural breaks as well as higher uncertainty. Thirdly and most interestingly from an economic perspective, an increased volatility in credit conditions (or higher cost of debt if the Moody's AAA corporate bond yields are applied) and the rising prices in commodities, both of which are associated with economic downturns, exacerbate realized volatility and those effects are intensified by a higher EPU.

8 Conclusions

Our study has examined the HEAVY model and extended it by taking into consideration leverage, power transformations, and macro characteristics. For the realized measure our empirical results favour the most general macro-augmented specification, where the lags of both powered variables - squared negative returns, and realized variance – drive the dynamics of the power transformed conditional variance of the latter. Similarly, modelling the returns with a double asymmetric power process, we found that not only the powered realized measure, but also the power transformed squared negative returns, help to forecast the conditional variance of the latter. The macro-augmentation of the asymmetric power model produces a specification that clearly outperforms its rivals and that can be used for the purposes of asset allocation and portfolio selection, as well as risk management. In particular, we show that it has a better out-of-sample forecasting performance over both short- and long-term horizons.

Finally, our analysis of the significant uncertainty effect on the power of leverage (Heavy and Arch), credit, and commodity determinants of realized variance, provides new evidence on i) the drivers of volatility and ii) macro-financial linkages. Our two main findings are the following: given higher (lower) daily uncertainty levels, mostly associated with economic downturns (upturns), i) heavy and leverage effects become more (less) pronounced in realized variance models, and ii) the impact of credit and commodity market conditions on financial volatility increases (decreases). Interestingly, the latter suggests that the positive effect of tighter credit conditions (proxied either by higher Treasury bonds volatility or higher corporate yields) and higher commodity prices (captured either by the commodity benchmark GSCI index or the crude oil WTI prices) on stock market volatility is amplified by higher economic policy uncertainty during periods of weakened economic conditions.

Our empirical findings on the nexus between low-frequency daily squared returns, high-frequency intra-daily realized measures and daily macro proxies provide a volatility forecasting framework with important implications for policymakers and market practitioners, from investors, risk and portfolio managers up to financial chiefs, and suggest possible avenues for future research to extend the HEAVY model further. Our framework can be used by both policymakers and market players to analyse and forecast financial volatility patterns with the aim of designing policies to preserve financial stability, and deciding on asset allocation, hedging strategies, and investment projects.

Our future work will extend the analysis to exchange rates and other asset classes using in each case appropriate macro proxies for volatility. It would also be interesting to construct daily EPU indices for other countries, in addition to the US and the UK, to obtain wider evidence. Finally, another possibile direction for future research would focus on extending the multivariate HEAVY specification of Noureldin et al. (2012) with leverage, power transformations and macro effects, starting from the recent study of

Dark (2018), who has applied the Dynamic Conditional Correlations multivariate GARCH models (Engle, 2002a) to the multivariate HEAVY, or Opschoor et al. (2018) within the Generalized Autoregressive Score (GAS) process of Creal et al. (2013).

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A APPENDIX

A.1 Realized Measure Equation Analysis

Table A.1: The (m-)DAP-HEAVY-R equation.

	SP	DJ	NASDAQ	RUSSELL	FTSE
Panel A. Realized Measure: DAP-HEAVY- R					
$(1-\beta_R L)(\sigma^2_{Rt})^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{RR} + \gamma_{RR}s_{t-1})L(RM_t)^{\frac{\delta_R}{2}} + \gamma_{Rr}s_{t-1}L(r_t^2)^{\frac{\delta_r}{2}}$					
β_R	0.66 (30.45)***	0.71 (36.12)***	**0.56** (24.55)***	0.63 (25.96)***	0.77 (38.05)***
α_{RR}	0.23 (11.61)***	0.19 (11.12)***	0.33 (16.15)***	0.24 (11.70)***	**0.14** (6.32)***
γ_{RR}	0.06 (5.40)***	0.07 (5.47)***	**0.02** (2.09)***	0.08 (6.61)***	0.04 (2.91)***
γ_{Rr}	0.09 (9.24)***	0.09 (7.85)***	0.07 (11.85)***	**0.03** (6.95)***	0.08 (10.39)***
lnL	-5657.92	-5707.67	-5916.68	-5073.43	-5846.08
Panel B. Realized Measure: m-DAP-HEAVY- R with EPU only					
$(1-\beta_R L)(\sigma^2_{Rt})^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{RR} + \gamma_{RR}s_{t-1})L(RM_t)^{\frac{\delta_R}{2}} + \gamma_{Rr}s_{t-1}L(r_t^2)^{\frac{\delta_r}{2}} + \phi_R EPU_{t-1}$					
β_R	0.66 (30.13)***	0.70 (35.47)***	**0.56** (24.15)***	0.62 (25.08)***	0.77 (37.69)***
α_{RR}	0.23 (11.65)***	0.19 (11.13)***	0.33 (16.14)***	0.24 (11.76)***	**0.14** (6.49)***
γ_{RR}	0.06 (5.41)***	0.07 (5.43)***	**0.02** (2.11)***	0.08 (6.66)***	0.04 (3.00)***
γ_{Rr}	0.09 (9.34)***	0.09 (7.89)***	0.07 (11.88)***	**0.03** (6.95)***	0.08 (10.41)***
ϕ_R	0.02 (4.57)***	**0.01** (1.78)**	**0.01** (1.52)*	0.02 (2.71)***	**0.01** (2.42)***
lnL	-5657.55	-5707.50	-5916.60	-5073.06	-5845.72
Powers δ_i					
δ_r	**1.40**	**1.40**	1.50	**1.40**	1.50
δ_R	**1.30**	**1.30**	**1.30**	**1.30**	**1.30**

Notes: See Notes in Table 2.

Table A.2: The Benchmark HEAVY-R equation

with EPU, Bonds & Commodities.

$$(1-\beta_R L)\sigma^2_{Rt} = \omega_R + \alpha_{RR} L(RM_t)$$
$$+\phi_R EPU_{t-1} + \zeta_R BO_{t-1} + \vartheta_R CO_{t-1}$$

	SP	DJ	NASDAQ	RUSSELL	FTSE
β_R	0.49 (12.42)***	0.53 (12.06)***	**0.43** (12.21)***	0.50 (13.77)***	$\underline{0.60}$ (14.44)***
α_{RR}	0.49 (11.53)***	0.45 (9.13)***	$\underline{0.54}$ (14.98)***	0.43 (12.93)***	**0.37** (8.99)***
ϕ_R	$\underline{0.03}$ (2.77)***	**0.02** (2.11)***	**0.02** (1.60)*	**0.02** (2.51)***	$\underline{0.03}$ (2.34)***
ζ_R	0.07 (3.25)*** $MOVE$	0.07 (3.12)*** $MOVE$	$\underline{0.12}$ (3.79)*** $M.AAA$	**0.06** (3.07)*** $MOVE$	0.07 (2.30)*** $MOVE$
ϑ_R	**0.03** (2.77)*** $GSCI$	0.04 (2.61)*** $GSCI$		$\underline{0.06}$ (4.21)*** WTI	
lnL	-5686.59	-5793.09	-6039.20	-5089.25	-5855.30

Notes: See notes in Table 2.

Table A.3: The m-DAP-HEAVY-R equation for SP with EPU, Bonds & Commodities (stepwise procedure).

$$(1-\beta_R L)(\sigma^2_{Rt})^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{RR} + \gamma_{RR} s_{t-1}) L(RM_t)^{\frac{\delta_R}{2}}$$
$$+\gamma_{Rr} s_{t-1} L(r_t^2)^{\frac{\delta_r}{2}} + \phi_R EPU_{t-1} + \zeta_R BO_{t-1} + \vartheta_R CO_{t-1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_R	0.66 (30.13)***	0.65 (28.11)***	0.66 (29.19)***	0.66 (28.87)***	0.66 (29.93)***	0.65 (27.72)***	0.65 (27.87)***	0.66 (28.60)***	0.66 (28.66)***
α_{RR}	0.23 (11.65)***	0.22 (10.93)***	0.22 (10.52)***	0.21 (10.67)***	0.23 (11.55)***	0.21 (10.19)***	0.22 (10.65)***	0.21 (10.29)***	0.21 (10.47)***
γ_{RR}	0.06 (5.41)***	0.07 (5.87)***	0.07 (5.88)***	0.07 (5.85)***	0.06 (5.42)***	0.07 (6.11)***	0.07 (5.92)***	0.07 (5.99)***	0.07 (5.90)***
γ_{Rr}	0.09 (9.34)***	0.09 (9.48)***	0.09 (9.59)***	0.09 (9.48)***	0.09 (9.38)***	0.09 (9.67)***	0.09 (9.58)***	0.09 (9.59)***	0.09 (9.55)***
ϕ_R	0.02 (4.57)***	0.02 (2.76)***	0.02 (3.88)***	0.03 (4.43)***	0.01 (2.26)***	0.02 (3.74)***	0.01 (2.25)***	0.03 (4.53)***	0.03 (4.06)***
ζ_R		0.07 (5.43)*** $MOVE$		0.09 (5.92)*** AAA		0.06 (4.26)*** $MOVE$	0.08 (5.72)*** $MOVE$	0.07 (3.63)*** AAA	0.10 (6.11)*** AAA
ϑ_R			0.04 (5.79)*** $GSCI$		0.01 (1.41) WTI	0.03 (4.41)*** $GSCI$	0.02 (2.69)*** WTI	0.02 (2.94)*** $GSCI$	0.02 (2.28)*** WTI
δ_r					1.40				
δ_R					1.30				
AIC	2.35120	2.35086	2.35093	2.35081	2.35158	2.35080	2.35114	2.35108	2.35113

Notes: See notes in Table 2.

A.2 Stock Index, Macro variables and Residuals Graphs

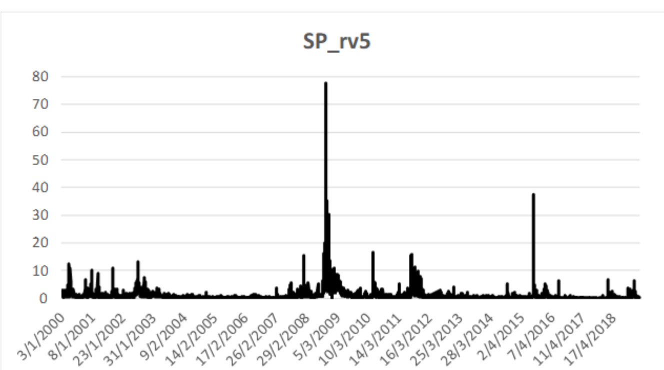


Figure A.1. S&P 500 Realized Variance

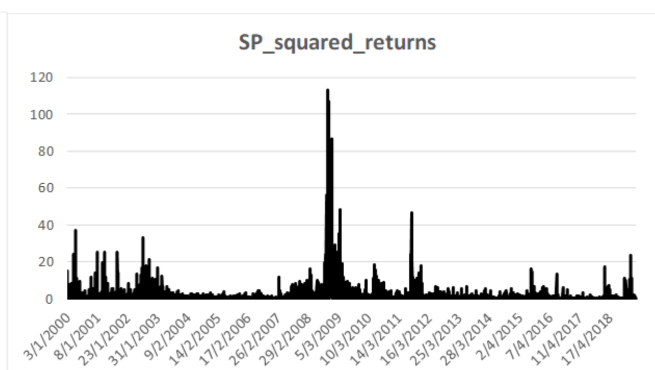


Figure A.2. S&P 500 Squared Returns

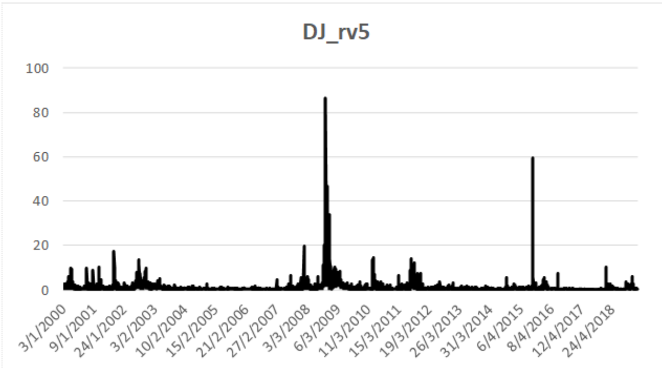


Figure A.3. Dow Jones Realized Variance

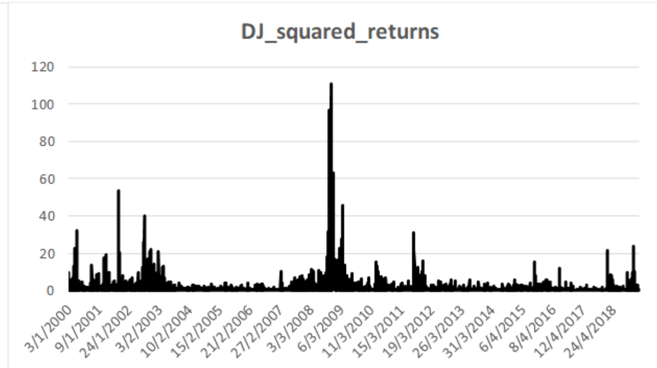


Figure A.4. Dow Jones Squared Returns

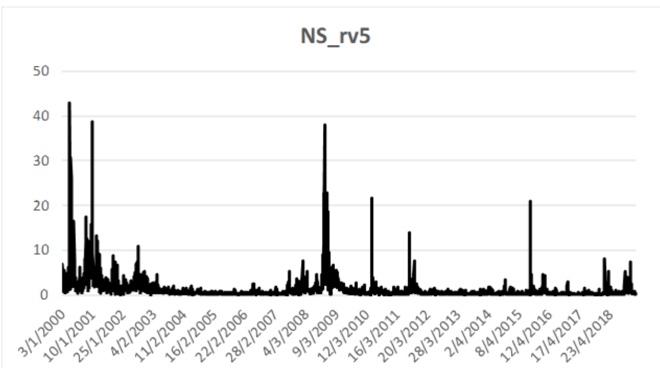


Figure A.5. Nasdaq 100 Realized Variance

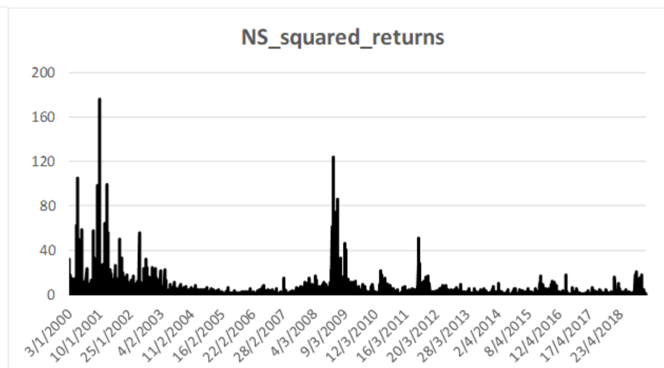


Figure A.6. Nasdaq 100 Squared Returns

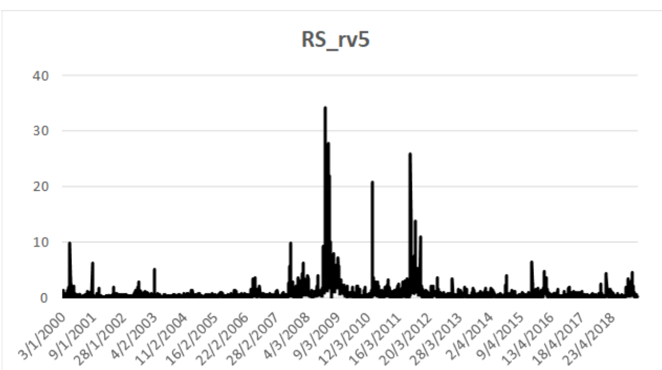


Figure A.7. Russell 2000 Realized Variance

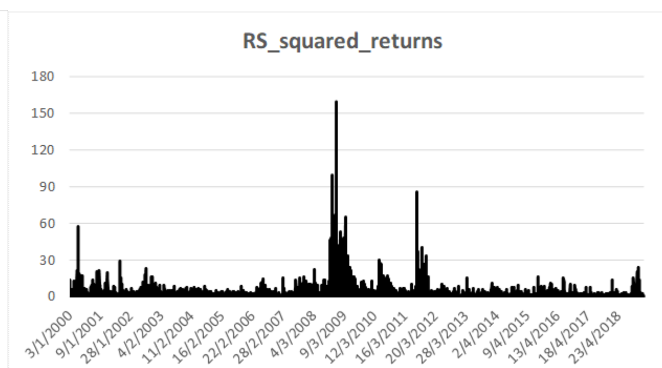


Figure A.8. Russell 2000 Squared Returns

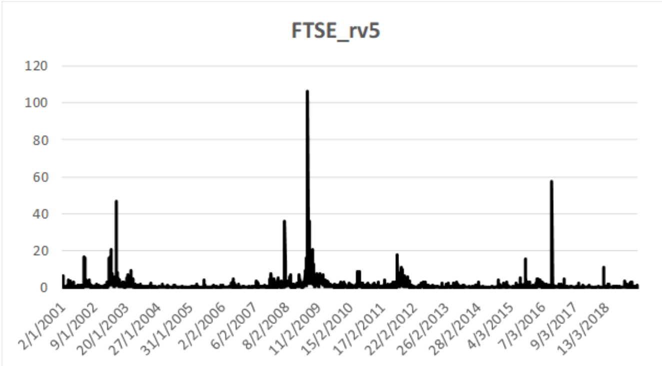


Figure A.9. FTSE 100 Realized Variance

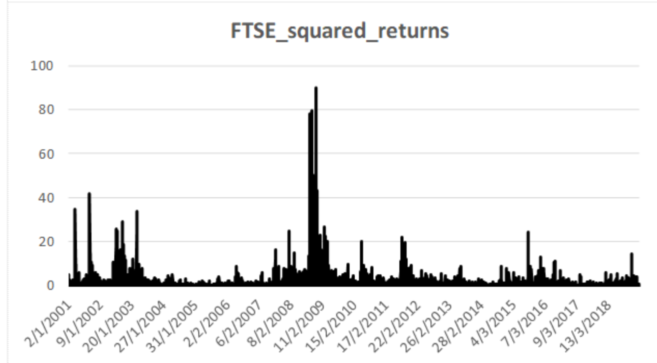


Figure A.10. FTSE 100 Squared Returns

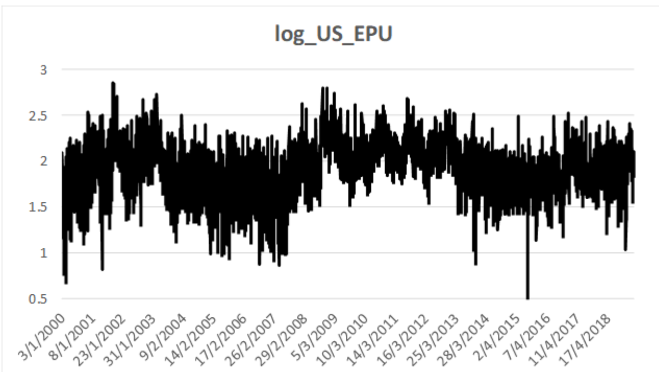


Figure A.11. US Economic Policy Uncertainty

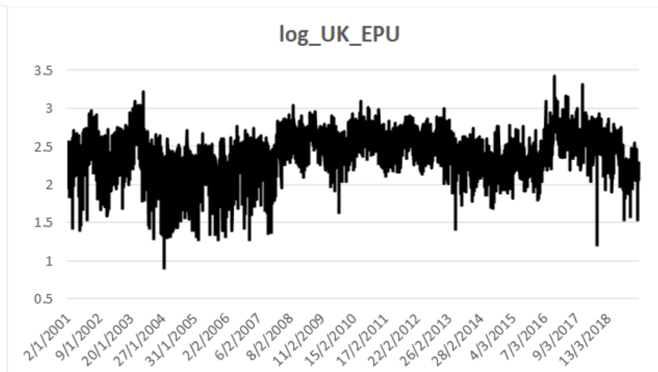


Figure A.12. UK Economic Policy Uncertainty

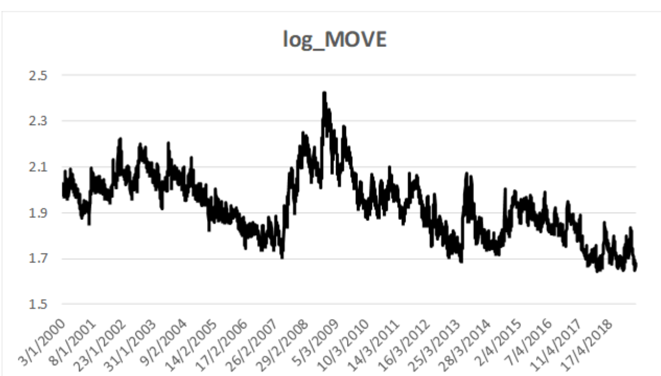


Figure A.13. Merrill Lynch MOVE 1 Month

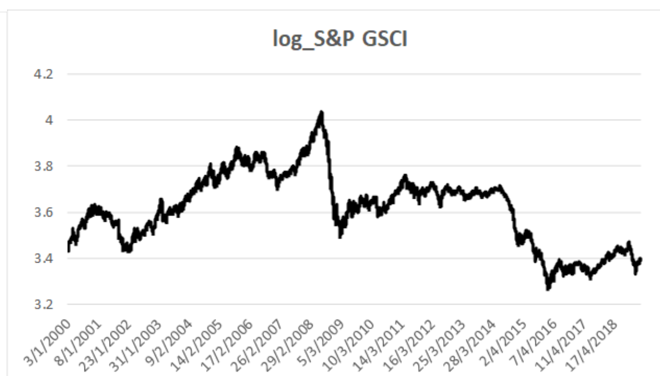
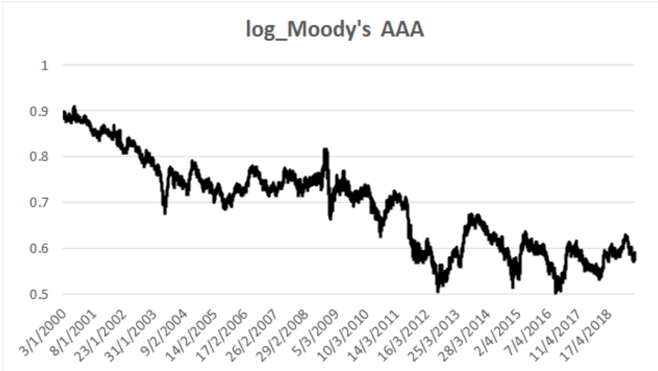


Figure A.14. S&P GSCI



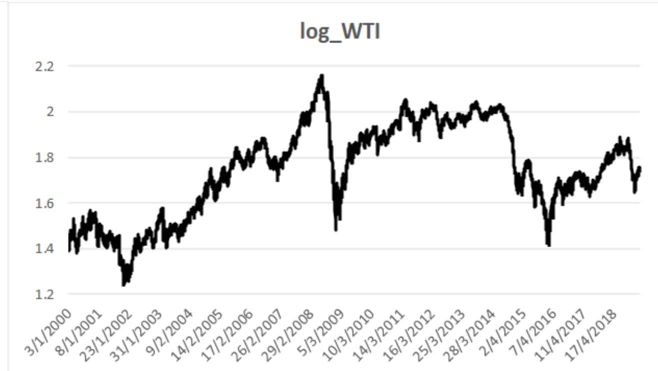


Figure A.15. Moody's AAA corporate bonds yield

Figure A.16. Crude oil WTI

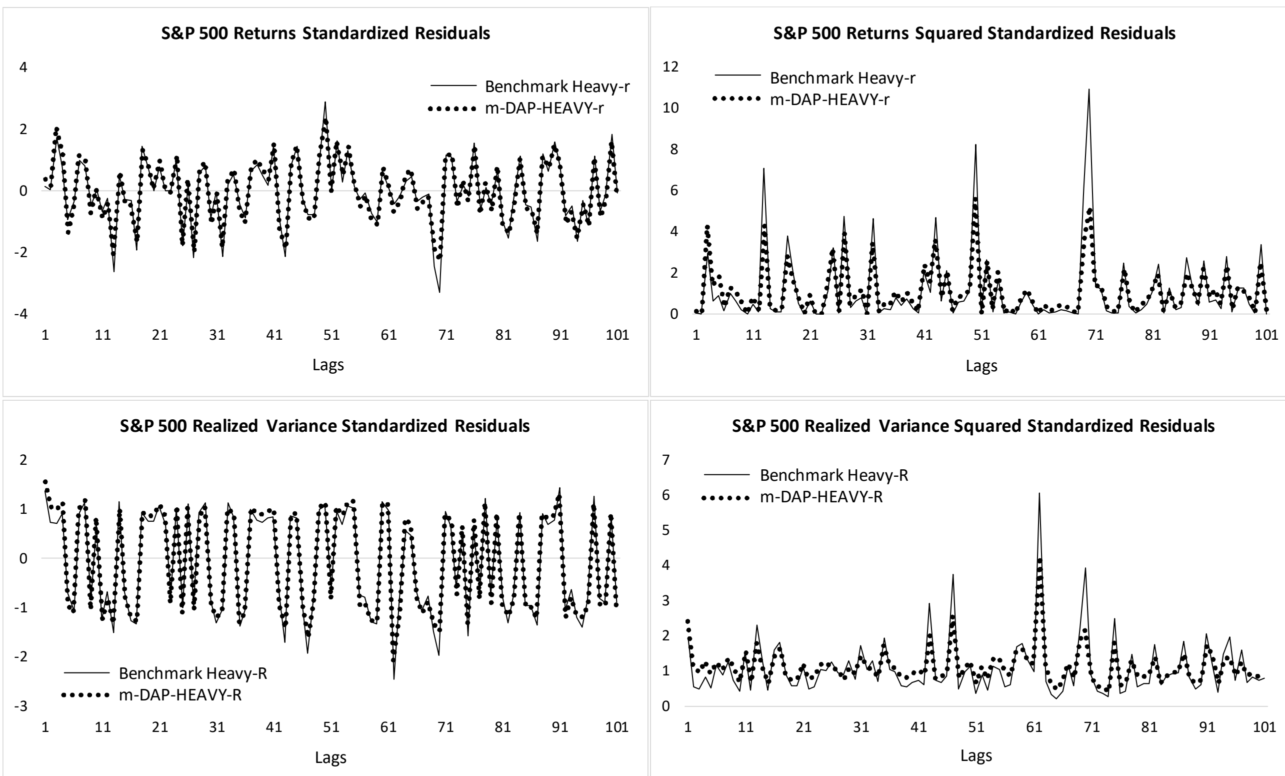


Figure A.17. S&P 500 Standardized Residuals (Benchmark HEAVY and m-DAP-HEAVY models)