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Guglielmo Maria Caporale, Menelaos Karanasos and Stavroula Yfanti

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

Guglielmo Maria Caporale[†], Menelaos Karanasos[‡], Stavroula Yfanti[‡]

[†]Brunel University London, UK; [‡]Loughborough University, UK

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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

[†] Address for correspondence: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University London, Uxbridge UB8 3PH, UK Telephone: +44 (0)1895 266713. Email: Guglielmo-Maria.Caporale@brunel.ac,uk

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 …nancial 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 …nancial economics, such as bonds investing, foreign exchange trading and commodities hedging, and core daily functions in the treasuries of most …nancial and non-…nancial corporations. Speci…cally, it outperforms the benchmark speci…cation 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 …nancial 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 speci…cation, which allows for asymmetries, power transformations, and macro e¤ects. 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 e¤ects on the parameters of the HEAVY speci…cations. Finally, Section 8 o¤ers 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 (051)-lta. And((051)-l2gVi-26al.)-432lta.sphara. and (051)--27(deleap)-28(er)-29al ar

The financial econometrics literature on realized volatility mostly ignores important macro factors

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 re‡ect-1(nfoi-1(nfoi-1(nfoi-1(

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), …rm 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 speci…cations 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 …nancial 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 measure as follows: $\widetilde{RM}_t = \text{sign}(r_t)\sqrt{RM_t}$, where $\text{sign}(r_t) = 1$, if $r_t > 0$ and $\text{sign}(r_t) = -1$, if $r_t < 0$.

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

$$r_t = e_{rt}\sigma_{rt}; \quad \widetilde{RM}_t = e_{Rt}\sigma_{Rt}; \tag{1}$$

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 $F_{t-1}^{(XF)}$, that is the filtration generated by all available information through time $t-1$. We will use $F_{t-1}^{(HF)}$ $(X = H)$ for the high-frequency past data, i.e., for the case of the realized measure, or $F_{t-1}^{(LoF)}$ $(X = Lo)$ 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

$$E(r_t^2 | F_{t-1}) = \sigma_{rt}^2, \text{ and } E(\widetilde{RM}_t^2 | F_{t-1}$$

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 speci…cation, where the only unconditional regressor is the …rst lag of the powered RM_t.

Next, we provide a comparison between the benchmark HEAVY system and the more general AP speci…cation. Their di¤erence is captured by the matrix 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 speci…cation, C is a full matrix with: i) diagonal elements given by $\ _i + (\ _{ii} + \ _{ii}=2)z_i$, $i = r; R$, where $z_i = E(je_{it}j^{\ i}$, and ii) o¤-diagonal elements given by $(\ _{ij} + \ _{ij})z_j$, $i; j = r; R$, for $i \neq j$. For the benchmark model, since $\ _{ij} = 0$, $z_i = 1$, for all $i; j = r; R$, and $\ _{Rr} = 0$, C is restricted to being an upper diagonal matrix. That is, we have

$$\text{DAP Speci…cation:} \quad C = \begin{bmatrix} \ _r + (\ _{rr} + \ _{rr}=2)z_r & (\ _{rR} + \ _{rR}=2)z_R \\ (\ _{Rr} + \ _{Rr}=2)z_r & \ _R + (\ _{RR} + \ _{RR}=2)z_R \end{bmatrix}$$

$$\text{Benchmark HEAVY} : \quad C = \begin{bmatrix} \ _r & \ _{rR} \\ 0 & \ _R + \ _{RR} \end{bmatrix}:$$

Figure 1 presents the comparison of the benchmark and DAP-HEAVY models' forecasting performance (see also Section 6). We apply the optimal predictor $\widehat{jr_tj}$ (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 speci…cation produces forecasts signi…cantly 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 signi…cant 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

speci…cation without the direct e¤ect from the macro variables $(_r ;\ _r ; \#_r = 0)$.

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:

$$\text{HEAVY-}r: \ (1 \quad {}_r L) \ {}^{2}_{rt} = !_r + \ {}_{rR} L(RM_t);$$
$$\text{HEAVY-}R: \ (1 \quad {}_R L) \ {}^{2}_{Rt} = !_R + \ {}_{RR} L$$

(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: $r_t = [\ln(P_t^C) - \ln(P_{t-1}^C)] \cdot 100$, 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).

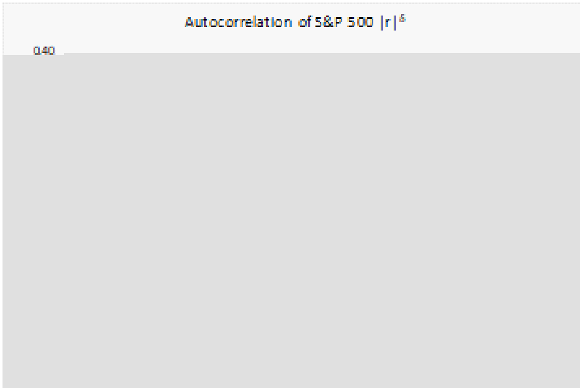

Figure 2. Autocorrelation of S&P 500 $|r_t|^{\delta_r}$ for $\delta_r = 1.4; 1.7; 2.0$

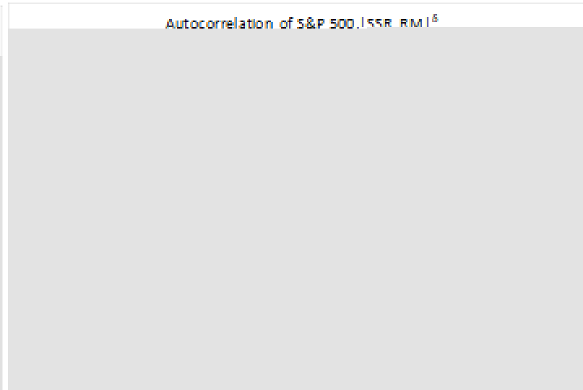

Figure 3. Autocorrelation of S&P 500 $|SSR\_RM_t|^{\delta_R}$ for $\delta_R = 1.3; 1.6; 2.0$

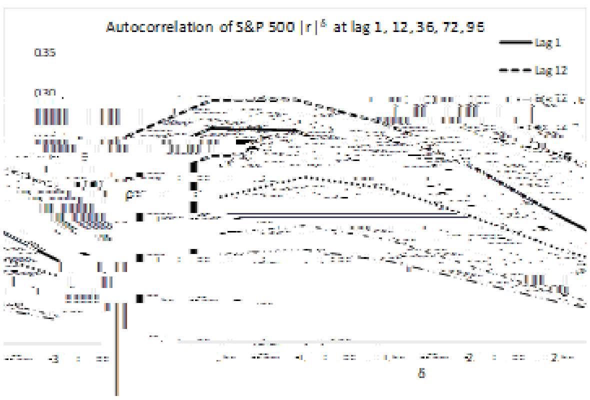

Figure 4. Autocorrelation of S&P 500 $|r_t|^{\delta_r}$ at lags 1; 12; 36; 72; 96

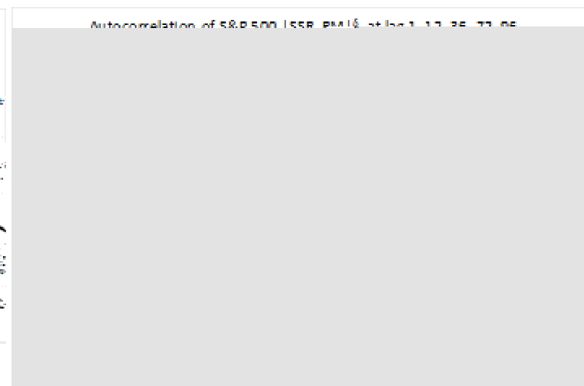

Figure 5. Autocorrelation of S&P 500 $|SSR\_RM_t|^{\delta_R}$ at lags 1; 12; 36; 72; 96

4.3 Macroeconomic Proxies

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 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

Figure 7. UK EPU and FTSE 100 Realized Variance

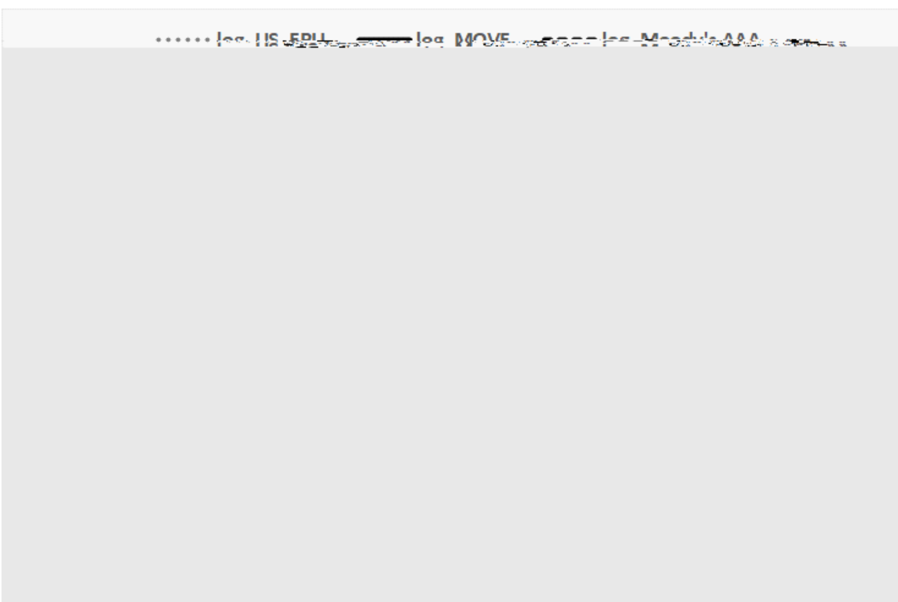

Figure 8. US EPU and the Credit market proxies

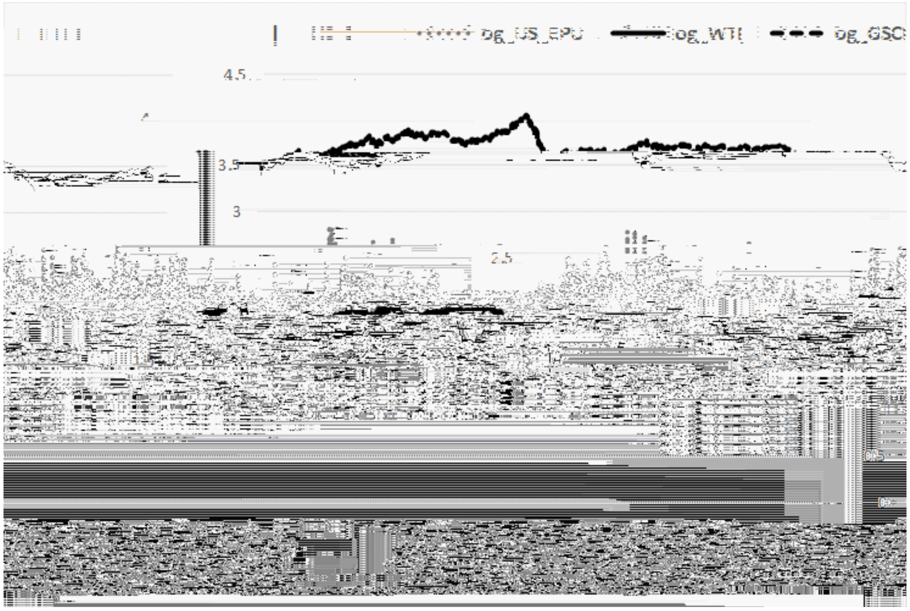

Figure 9. US EPU and the Commodity market proxies

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 signi…cant but should be excluded from the model because the negative sign of the relevant coe¢ cient 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 …nancial volatility. Finally, the realized variance is a¤ected 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 di¤erence 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, …nancial volatility is a¤ected 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-…nancial 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 speci…cation 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, $_{rr}$, 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 $_{rR}$, high in value and significant for all indices. The momentum parameter, $_{r}$, 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, $_{RR}$, is estimated between 0.37 and 0.54 and the momentum, $_{R}$, 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

Table 2: The Benchmark HEAVY model.

	SP	DJ	NASDAQ	RUSSELL	FTSE
Panel A. Stock Returns: HEAVY- r					
$(1 \quad {}_r L)\ {}^{2}_{rt} = !_r + {}_{rR} L(RM_t)$					
r	0:63	0:66	0:65	0:70	0:64
	(12:56)	(15:77)	(12:36)	(18:92)	(14:08)
rR	0:48	0:39	0:65	0:71	0:38
	(6:83)	(7:38)	(6:30)	(7:65)	(7:22)
Q_{12}	16:72	15:19	15:43	13:69	4:65
	[0:08]	[0:23]	[0:22]	[0:19]	[0:97]
SBT	2:46	1:60	1:59	1:87	2:57
	[0:01]	[0:11]	[0:11]	[0:06]	[0:01]
lnL	6364:15	6180:79	7611:05	7998:95	6067:59
Panel B. Realized Measure: HEAVY-R					
$(1 \quad {}_R L)\ {}^{2}_{Rt} = !_R + {}_{RR} L(RM_t)$					
R	0:52	0:57	0:44	0:54	0:62
	(13:52)	(13:64)	(13:20)	(14:92)	(15:99)
RR	0:48	0:44	0:54	0:42	0:37
	(10:99)	(9:00)	(14:96)	(12:34)	(8:96)
Q_{12}	12:64	11:85	7:87	19:97	10:23
	[0:40]	[0:46]	[0:80]	[0:07]	[0:60]
SBT	4:64	3:70	2:47	3:13	2:68
	[0:00]	[0:00]	[0:01]	[0:00]	[0:01]
lnL	5691:96	5798:58	6040:92	5093:92	5858:93

Notes: The numbers in parentheses are t-statistics.

, , denote signi…cance at the 0:05, 0:10, 0:15

level, respectively. Bold (underlined) numbers indicate

minimum (maximum) values across the …ve indices. Q_{12} is

the Box-Pierce Q-statistics on the standardized residuals tries. We estimate the power terms separately with a two-stage procedure, as follows: …rst, we estimate univariate asymmetric power speci…cations for the returns and the realized measure; the Wald tests for the estimated power terms (available upon request) reject the hypotheses of $_i = 1$ and $_i = 2$ in most cases. In the second stage, we use the estimated powers805 -1.494 Td37

daily term spread, a reliable predictor of GDP (Estrella and Hardouvelis, 1991) and signi…cant in the monthly context as evidenced by Conrad and Loch (2015). Based on the rich empirical evidence of the adverse uncertainty e¤ects 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 speci…cations for the EPU variable is in accordance with prior …ndings on the positive e¤ect of macroeconomic uncertainty (Schwert, 1989) and unemployment, and the negative e¤ect 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 e¤ect 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 …nancing for …rms and investors and, consequently, reduce activity. Accordingly, the global bond factor coe¢ cients 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 signi…cant in most cases. Given the evidence on e¤ects of commodity prices on the macroeconomy (see, for example, Barsky and Kilian, 2004), we also include them and …nd a destabiliz-391(8vl331(pr,)-348dese45(as)-1(so)

Table 3: The m-DAP-HEAVY model.

	SP	DJ	NASDAQ	RUSSELL	FTSE

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 speci…cation 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 e¤ects using either static or dynamic forecasts. Finally, for the 1-month forecasts, the mall

Table 4: Mean Square Error (MSE) of m-step ahead forecasts

for SP as a Ratio of the benchmark model.

Speci…cations# 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 di¤erent speci…cations.

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

for SP as a Ratio of the benchmark model.

95% con…dence 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 speci…c 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 con…dence level (the 99% and 95% con…dence 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 …nancial institutions since regulators heavily penalize banks' internal models that fail to cover trading losses through the VaR estimates. Following the Basel tra¢ c 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% con…dence 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 speci…cation (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 speci…cations, 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 in‡ating 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	
Speci…cations	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	65:11	107:50	46:03	76:01
m-DAP with EPU	1	3	65:24	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 speci…cations 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 …nance 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

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) $_{RR}^{epu}$ is the parameter of the lagged EPU multiplied by the lagged realized variance asymmetries, capturing the EPU effect on the own Heavy asymmetry coefficient (

Table 7: The m-DAP-HEAVY- R equation for SP with the EPU e¤ect on

Heavy, Arch and Macro parameters.

$$(1 \quad _{R}L)(\, ^{2}_{Rt})^{\frac{R}{2}} = ! \, _{R} + [\, _{RR} + (\, _{RR} + \, ^{epu}_{RR}EPU_{t \quad 1})s_{t \quad 1}]L(RM_{t})^{\frac{R}{2}} +$$
$$(\, _{Rr} + \, ^{epu}_{Rr}EPU_{t \quad 1})s_{t \quad 1}L(r_t^2)^{\frac{r}{2}} + (\, _{R} + \, ^{epu}_{R}EPU_{t \quad 1})BO_{t \quad 1} +$$
$$(\#_R + \#_R^{epu}EPU_{t \quad 1})CO_{t \quad 1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)
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)
RR				0:07 (6:23)	0:07 (5:88)	0:07 (6:12)	0:07 (5:87)	0:07 (6:11)
$^{epu}_{RR}$	0:04 (5:92)	0:04 (5:66)	0:04 (5:66)	0:04 (3:53)				
Rr				0:09 (9:56)	0:09 (9:49)	0:09 (9:68)	0:09 (9:59)	0:09 (9:68)
$^{epu}_{Rr}$	0:05 (9:32)	0:05 (9:34)	0:05 (9:35)					
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
$^{epu}_{R}$		0:01 (1:54) MOVE			0:01 (2:84) MOVE	0:01 (3:79) MOVE		
$\#_R$	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
$\#_R^{epu}$			0:003 (1:61) GSCI				0:01 (3:95) GSCI	0:01 (3:80) GSCI
r				1:40				
R				1:30				

Notes: See notes in Table 2. Superscripts indicate the EPU e¤ect 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 …rstly prove the EPU destabilizing impact7 Td [9bl Tds6(to2)-7(2)-inkk(2)-eistsl Tdw(Wink)058[(…)12na8(n)(ciical)058v(2)

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 speci…cation, 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 speci…cation 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 signi…cant uncertainty e¤ect 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-…nancial linkages. Our two main …ndings are the following: given higher (lower) daily uncertainty levels, mostly associated with economic downturns (upturns), i) heavy and leverage e¤ects become more (less) pronounced in realized variance models, and ii) the impact of credit and commodity market conditions on …nancial volatility increases (decreases). Interestingly, the latter suggests that the positive e¤ect 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 ampli…ed by higher economic policy uncertainty during periods of weakened economic conditions.

Our empirical …ndings 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 …nancial chiefs, and suggest possible avenues for future research to extend the HEAVY model further.

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					
$(1 \quad {}_R L)({}^2_{Rt})^{\frac{R}{2}} = !_R + ({}_{RR} + {}_{RR} s_{t \quad 1}) L (RM_t)^{\frac{R}{2}} + {}_{Rr} s_{t \quad 1} L (r_t^2)^{\frac{r}{2}}$					
R	0:66 (30:45)	0:71 (36:12)	0:56 (24:55)	0:63 (25:96)	0:77 (38:05)
RR	0:23 (11:61)	0:19 (11:12)	0:33 (16:15)	0:24 (11:70)	0:14 (6:32)
RR	0:06 (5:40)	0:07 (5:47)	0:02 (2:09)	0:08 (6:61)	0:04 (2:91)
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					
$(1 \quad {}_R L)({}^2_{Rt})^{\frac{R}{2}} = !_R + ({}_{RR} + {}_{RR} s_{t \quad 1}) L (RM_t)^{\frac{R}{2}} + {}_{Rr} s_{t \quad 1} L (r_t^2)^{\frac{r}{2}} + {}_R EPU_{t \quad 1}$					
R	0:66 (30:13)	0:70 (35:47)	0:56 (24:15)	0:62 (25:08)	0:77 (37:69)
RR	0:23 (11:65)	0:19 (11:13)	0:33 (16:14)	0:24 (11:76)	0:14 (6:49)
RR	0:06 (5:41)	0:07 (5:43)	0:02 (2:11)	0:08 (6:66)	0:04 (3:00)
Rr	0:09 (9:34)	0:09 (7:89)	0:07 (11:88)	0:03 (6:95)	0:08 (10:41)
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 $_i$					
r	1:40	1:40	1:50	1:40	1:50
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.

$$(1 \quad {}_{R}L)\ {}^{2}_{Rt} = !\,_{R} + \quad {}_{RR}$$

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

$$(1 \quad {}_R L)({}^{2}_{Rt})^{\frac{R}{2}} = !_R + ({}_{RR} + {}_{RR} s_{t \quad 1}) L (RM_t)^{\frac{R}{2}}$$

$$+ {}_{Rr} s_{t \quad 1} L(r_t^2)^{\frac{r}{2}} + {}_R EPU_{t \quad 1} + {}_R BO_{t \quad 1} + \#_R CO_{t \quad 1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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)
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)
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)
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)
R	0:02 (4:57)	0:02 (2:76)	0:02 (3:88)	0:03 (4:					

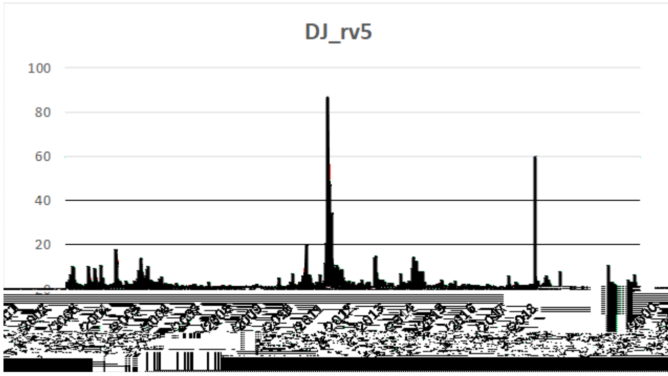

Figure A.3. Dow Jones Realized Variance

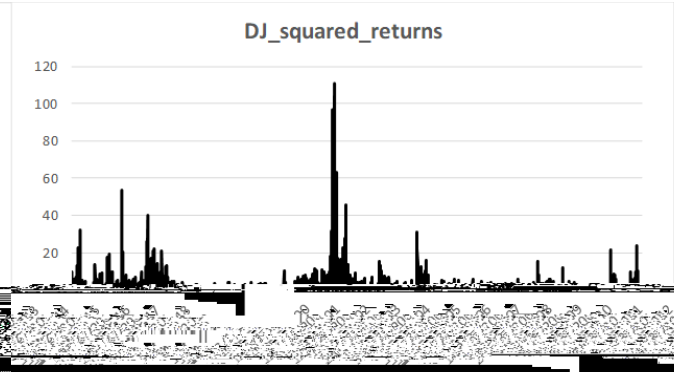

Figure A.4. Dow Jones Squared Returns

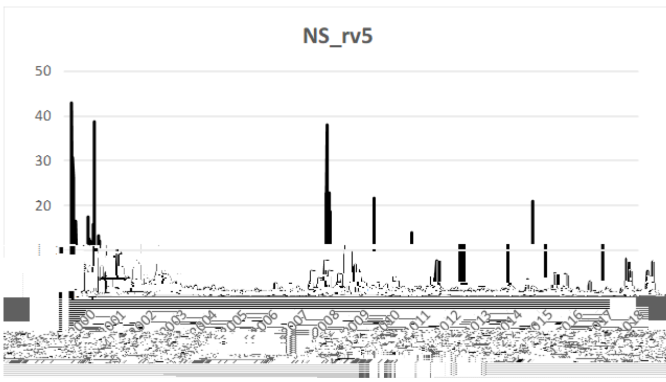

Figure A.5. Nasdaq 100 Realized Variance

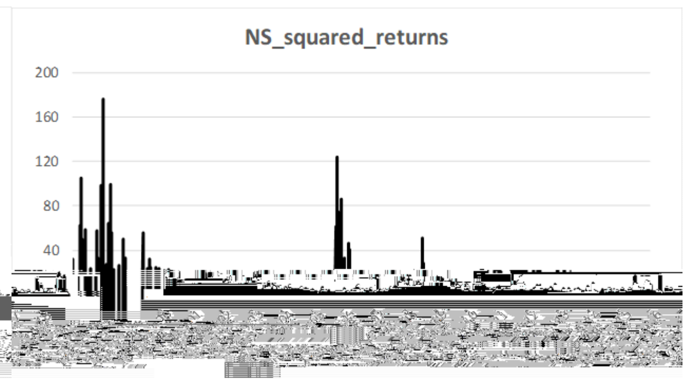

Figure A.6. Nasdaq 100 Squared Returns

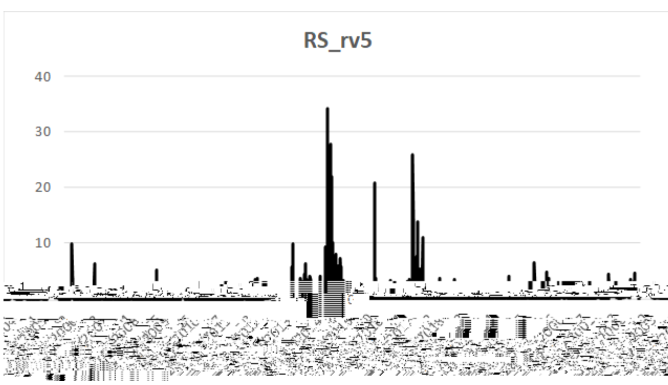

Figure A.7. Russell 2000 Realized Variance

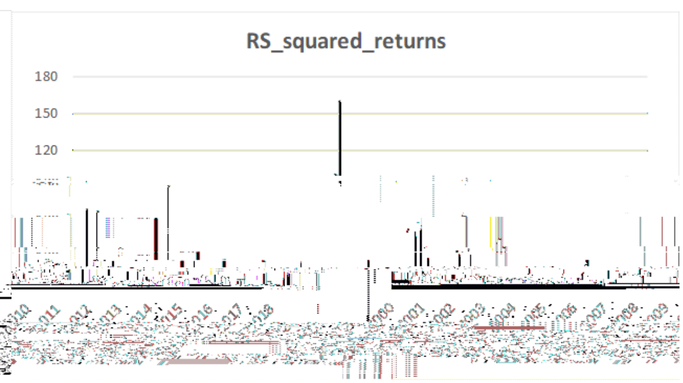

Figure A.8. Russell 2000 Squared Returns

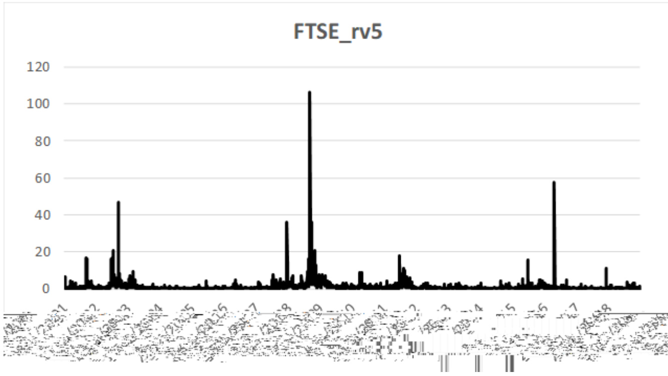

Figure A.9. FTSE 100 Realized Variance

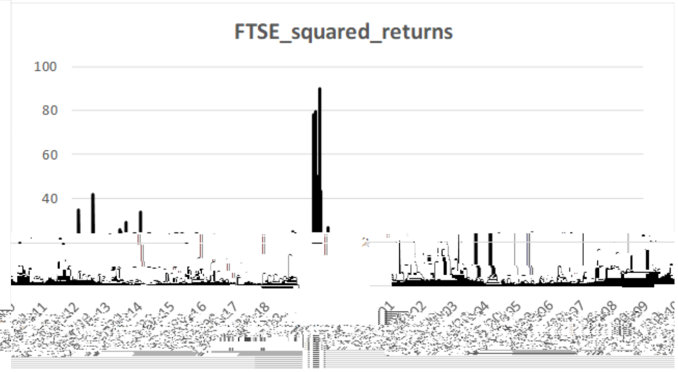

Figure A.10. FTSE 100 Squared Returns

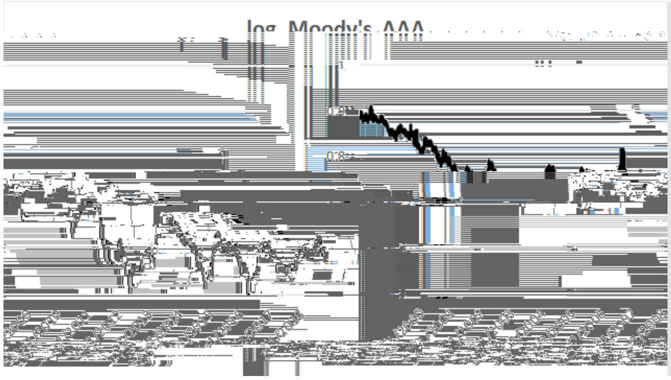

Figure A.15. Moody's AAA corporate bonds yield

Figure A.16. Crude oil WTI

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