Macro-financial Linkages in the High-Frequency Domain:

Economic fundamentals and the Covid-induced uncertainty channel

in US and UK financial markets.

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Abstract

This paper contributes to our understanding of the macro-financial linkages in the high-frequency domain during the recent health crisis. Building on the extant literature that mainly uses monthly or quarterly macro proxies, we examine the daily economic impact on intra-daily financial volatility by applying the macro-augmented HEAVY model with asymmetries and power transformations. Our study associates US and UK financial with macroeconomic uncertainties in addition to further macro drivers that exacerbate equity market volatility. Daily local economic policy uncertainty is one of the main drivers of financial volatility, alongside global credit and commodity factors. Higher macro uncertainty is found to increase the leverage and macro effects from credit and commodity markets on US and UK stock market realized volatility. Most interestingly, the Covid-19 outbreak is found to exert a considerable impact on financial volatilities through the uncertainty channel, given the prevalent worry about controversial policy interventions to support societies and markets, particularly in the case of the severely censured US and UK governments' reluctant and limited response in the very beginning of the pandemic.

Keywords: Covid-19 crisis, economic policy uncertainty, macro-financial linkages, realized variance, risk management.

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

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1 Introduction

Modeling and forecasting financial volatility are both of crucial importance to market practitioners for the purposes of derivatives pricing, portfolio management, firm valuation, and funding strategies, among others. Any business operation that includes asset valuation or risk assessment requires a volatility input. The behavior of volatility is also closely monitored by policymakers, given its potentially destabilizing effects on the financial system and the tight link of financial markets with the macroeconomic environment. 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 modeling framework that, apart from the time series properties of the second moment of returns, also considers significant macro fundamentals.

In this vein, our study investigates the macro-financial linkages in the high-frequency domain. In particular, we explore the daily macroeconomic effect on US and UK financial markets. We demonstrate that the stock market volatility receives the significant impact of daily macro fundamentals in all states of the economy and the recent pandemic-induced turmoil as well, by applying a sophisticated macro-augmented econometric framework for volatility modeling. We intend to contribute to the extant literature on the macro forces driving financial markets, by incorporating high-frequency (daily) economic proxies (rather than quarterly or monthly variables most commonly used), and on the Covid-19 crisis effects on the volatility pattern, by using a broad sample which covers the initial shock of the virus outbreak on the financial system. The economic environment is rapidly evolving, especially during crises. The necessity to nowcast the macroeconomic developments has become a critical challenge nowadays for both market practitioners in trading and investments and policymakers in market interventions (Berger et al., 2023). Macro-informed volatility forecasts should rely on timely published high-frequency fundamentals rather than the traditional monthly or quarterly indicators often released with a significant time lag.

Against this backdrop, we address this highly topical and policy-relevant issue by applying an extension of the HEAVY model of Shephard and Sheppard (2010)[1] introduced by Karanasos and Yfanti (2020) for financial volatility modeling, which augments the bivariate system with asymmetries and power transformations through the APARCH (Asymmetric Power Autoregressive Conditional Heteroskedasticity) 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) standard GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model (Brooks et al., 2000). The present study provides evidence that the augmented specification outperforms the benchmark one for the US and UK equity indices (see also Karanasos and Yfanti, 2020, for evidence on the European stock markets, and Karanasos et al., 2022, on emerging markets). Our first finding on US and UK equity data confirms the results of Karanasos and Yfanti (2020) for the European markets: namely, each of the two power transformed conditional variances is affected by the lags of both powered variables, the squared negative returns and the realized variance.

Second, we estimate the extension of the asymmetric power specification with macro effects from daily US and UK economic policy uncertainty, global credit and commodity market benchmarks. This is the way to explore macro-financial linkages with higher- than monthly- or quarterly-frequency macro factors (used in most of the existing empirical literature) and provide a robust volatility modeling framework directly applicable to the well-established practice of financial trading and risk measuring relying on relevant fundamentals from the real economy. We apply the macro-augmented model to five US and UK stock index time series data covering the last two decades, with the first five months of the current pandemic included. We find that realized volatility is significantly affected by the macro variables and their inclusion improves the model's forecasting performance. In contrast with Karanasos and Yfanti (2020) and Karanasos et al. (2022), who explore the UK- and US-led uncertainty spillovers over the European and emerging markets, respectively, our motivation here is to investigate the crucial role of the local uncertainty effect (US and UK uncertainties on US and UK stock markets, respectively) and emphasize the need for daily news-based uncertainty indices covering more countries than only the UK and the US.

Moreover, we estimate, apart from the direct destabilizing impact of uncertainty on volatility (by using it as a regressor), the uncertainty effect on each parameter of the realized volatility equation and demonstrate that higher uncertainty magnifies the leverage and macro effects from credit and commodity markets. Finally, we explore the daily macro-financial linkages separately during the world-wide Coronavirus outbreak. The Covid-19 effect on financial markets is significant and drives equity volatilities higher, mainly through the policy uncertainty channel, in line with the results of Baker et al. (2020a,b). The forecasting superiority of our approach is further illustrated through a Value-at-Risk (VaR) exercise focused particularly on the Covid period. In a nutshell, we answer three research questions. Which daily macro

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

fundamentals drive the US and UK stock market intra-daily volatility? Does the local uncertainty channel magnify the volatility drivers? How did the stock markets react to the initial pandemic wave?

Our study contributes to the existing macro-finance literature in two important areas: i) in volatility modeling, by implementing a novel macro-augmented econometric approach and demonstrating its superiority over standard benchmark models, and ii) in the investigation of macro-financial linkages with the effects of domestic uncertainty levels on the stability of US and UK financial markets, using high-frequency data and the Covid-induced impact. Hence, we demarcate our study from Karanasos and Yfanti (2020), who focus on European markets with the UK uncertainty level effects without the pandemic impact, and from Karanasos et al. (2022), who study the influence of the second moment (volatility) of the US uncertainty on emerging markets. The bivariate model of the two volatility series is suitable for equity market returns and several other financial assets, such as bonds, commodities or cryptocurrencies and business finance applications, such as investing and trading in bond and commodity markets, foreign exchange risk hedging and further important daily business operations of corporate treasuries. Specifically, it outperforms the benchmark specification in terms of both the 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 the VaR example that has both risk management and policy implications. Lastly, this paper is relevant to a crucial issue nowadays, the pandemic-induced crisis, and contributes to the burgeoning research on the Covid-19 socio-economic impact and policy interventions.

The remainder of the paper is structured as follows. Section 2 presents the theoretical background and our research hypotheses. Section 3 describes the extended HEAVY specification, which allows for asymmetries, power transformations, and macro effects. Section 4 describes our dataset and Section 5 presents the results for the benchmark and the macro-augmented asymmetric power models. Section 6 analyzes the forecasting properties of the alternative models by comparing their multiple-step-ahead forecasts and by using the volatility predictions in a VaR example for the Covid period. Section 7 focuses on the uncertainty effects on the parameters of the HEAVY specifications and Section 8 explores the recent Covid-induced uncertainty impact on macro-financial linkages. Finally, Section 9 offers some concluding remarks.

2 Theoretical Background and Research Hypotheses

In this Section, firstly, we outline our theoretical underpinnings in the existing literature, and, secondly, we develop our research hypotheses.

Theoretical Background

The harsh economic reality driven by the Covid-19 pandemic and the speed of the crisis spread introduce uncertainty into econometric modeling for the assessment of the disastrous effects of the virus outbreak (Baker et al., 2020c). Baker et al. (2020b) have measured this Covid-induced economic uncertainty feelings considering three major sources: equity volatility, newspaper-based and business expectations survey-based uncertainties. Baker et al. (2020a) have examined the pandemic's devastating impact on stocks and find that the effects are by far more potent than those of other health crises (e.g., Spanish flu) due to the current disease's severity, the faster spread of Covid-19 news, and the more solid cross-country macro-financial interdependence in the current globalized economic environment. In a broader context, Sharif et al. (2020) have explored the dependence structure between the pandemic, oil and stock market volatility, US policy uncertainty, and geopolitical tensions. Making use of the wavelet approach, they have shown, among others, the shocking Covid impact on equities volatility, geopolitical and policy uncertainty. Focusing on the Covid shock on equity volatility, Wang et al. (2020) have recently implemented an augmented HAR model (Heterogeneous Autoregressive) for stock market realized variance with two daily US uncertainties (the VIX index and the US Economic Policy Uncertainty) incorporated alternatively. Financial uncertainty, proxied by the VIX index, has been found more powerful at predicting worldwide equity index volatilities. This study has examined the cross-border spillovers of US uncertainty across various countries. In contrast, our work estimates the local uncertainty impact and further global macro effects on US and UK markets, employing the HEAVY model, a sophisticated econometric framework for both daily and intra-daily equity dispersion metrics.

Furthermore, a wide variety of literature has already shown the counter-cyclical pattern of stock market volatility using lower than daily-frequency macro drivers (see, for example, Schwert, 1989, Hamilton and Lin, 1996, Engle and Rangel, 2008, Engle et al., 2013, Corradi et al., 2013, Conrad and Loch, 2015). Motivated by this empirical evidence, we investigate how daily business cycle dynamics affect financial market stability. We first focus on the potent role of uncertainty alongside further macro forces. Uncertainty disrupts the real economy directly (e.g., output, employment, consumption, investment) and the financial markets, as well (see, among others, Bernanke, 1983, Dixit and Pindyck, 1994, Pastor and Veronesi, 2012, 2013, Bekaert et al., 2013, Bloom, 2014, Jurado et al., 2015, Han and Li, 2017, Carriero et al., 2018, Mumtaz and Theodoridis, 2018, Alessandri and Mumtaz, 2019, Jo and Sekkel, 2019, Bekiros et al., 2020). We choose the news-based index of Economic Policy Uncertainty (EPU), which is the only economic uncertainty metric available on a daily frequency by Baker et al. (2016) for two countries, namely, the United States and the United Kingdom (see also Karanasos and Yfanti, 2020, for the discussion on the relative merits of the EPU indices). We extend the studies of Karanasos and Yfanti (2020) and Karanasos et al. (2022), who first used the daily UK EPU index on European stock markets and the volatility of US EPU on emerging equities, by investigating the effect of both US and UK daily EPUs locally on US and UK equity volatility and their impact during the Covid-19 pandemic. Moreover, we incorporate daily global proxies for credit conditions and commodity markets to capture most aspects of the economic cycle.

Research Hypotheses

Our empirical analysis will respond to our three research questions about: i) the daily macro drivers of the US and UK stock market intra-daily volatility, ii) the impact of the local uncertainty channel on the volatility drivers, and iii) the initial pandemic shock on the stability of US and UK equity markets. Given the well-established literature on the counter-cyclicality of the volatility pattern, we test the following hypotheses:

Hypothesis 1. Weak (strong) daily macro fundamentals exacerbate (reduce) stock market volatility. (H1)

In our first Hypothesis, we expect that an economic slowdown captured by daily macro proxies destabilizes the US and UK stock markets. The volatility increases when economic uncertainty is higher, credit conditions are tighter, and commodities become more expensive. On the other hand, economic expansion is associated with markets 'tranquility' (see also, Section 4.2 for the discussion about the economic intuition supporting the selection of the macro variables which explain the volatility pattern).

Hypothesis 2. The local uncertainty channel magnifies the macro impact on stock market volatility. (H2)

In the second Hypothesis, we proceed with a sensitivity analysis by focusing on the EPU role. It is expected that an elevated local uncertainty level aggravates the impact of the volatility determinants (see, for example, Pastor and Veronesi, 2013).

Hypothesis 3. The pandemic shock intensifies the counter-cyclical behavior of stock market volatility. (H3)

Our final Hypothesis delves deeper into the macro-relevance of financial volatilities by examining their crisis vulnerability. We expect that the health crisis shock magnifies the macro impact on volatilities, and we confirm this counter-cyclical trajectory in the high-frequency domain.

3 The Econometric Framework

The financial econometrics literature has proposed a wide variety of volatility models. Andersen et al. (2001) and Barndorff-Nielsen et al. (2008) were the first to formalize realized volatility measures, while long memory models (ARFIMA and HAR-RV) are established for predicting the future volatility pattern (Andersen et al., 2001, Corsi, 2009). GARCH-X, HEAVY, and Realized GARCH are among the more sophisticated variance models which combine daily with intra-daily returns (Engle, 2002, Shephard and Sheppard, 2010, Hansen et al., 2012, Barunik et al., 2016). Based on the benchmark HEAVY bivariate specification of Shephard and Sheppard (2010), we implement the HEAVY extension introduced by Karanasos and Yfanti (2020), which considers asymmetries (downside risk), power transformations, and macro effects. We estimate the macro-augmented model incorporating these features in order to improve the performance of volatility forecasting (see also Karanasos et al., 2021, for a long memory HEAVY extension without macro effects, Yfanti et al., 2022, for a trivariate asymmetric power HEAVY system without macro effects, and Yfanti and Karanasos, 2022, for a tetravariate asymmetric HEAVY system without power transformations).

3.1 The HEAVY Model

Following the econometric representation of Karanasos and Yfanti (2020) and Karanasos et al. (2022), the HEAVY system of equations involves two variables: the close-to-close returns (r_t) and the realized measure based on high-frequency observations RM_t. Firstly, we calculate the signed square rooted (SSR) realized measure: $\widetilde{RM}_t = sign(r_t)\sqrt{RM_t}$, where $sign(r_t) = 1$, if $r_t \geq 0$ and $sign(r_t) = -1$, if $r_t < 0$.

Next, we make the following assumption for both returns and the SSR realized measure:

$$r_t = e_{rt}\sigma_{rt}, \widetilde{RM}_t = e_{Rt}\sigma_{Rt},$$

where the stochastic term e_{it} is considered 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 $\mathbb{F}_{t-1}^{(XF)}$, that is the filtration generated by all available information through time $t-1$. We will use $\mathbb{F}_{t-1}^{(HF)}$ $(X = H)$ for the high-frequency past data, i.e., for the case of the realized measure, or $\mathbb{F}_{t-1}^{(LoF)}$ $(X = Lo)$ for the low-frequency past data, i.e., for the case of the close-to-close returns. Hereafter, we will drop the superscript XF for notational convenience.

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

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

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) model for the HEAVY(1,1) system consists of the following equations (in what follows, we drop the order of the model if it is (1,1) for notational simplicity):

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

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, $(\sigma_{it}^2)^{\frac{\delta_i}{2}}$, is a linear function of the lagged values of the powered transformed squared returns and realized measure.

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

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

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

Moreover, all the parameters in this bivariate model should take non-negative values (see, for example, Conrad and Karanasos, 2010). We augment the realized measure equation with non-negative macro factors: the Economic Policy Uncertainty, EPU_t, the Credit conditions (the Merrill Lynch MOVE treasury bonds implied volatility index or the Moody's AAA corporate bonds yields), CR_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 given by the following equation for the realized variation measure:

$$(1 - \beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{Rr} + \gamma_{Rr} s_{t-1}) L (r_t^2)^{\frac{\delta_r}{2}} + (\alpha_{RR} + \gamma_{RR} s_{t-1}) L \big(RM_t\ \big)^{\frac{\delta_R}{2}} +$$

$$+ \varphi_R EPU_{t-1} + \zeta_R CR_{t-1} + \vartheta_R CO_{t-1}. \qquad (2)$$

Eq. (2) incorporates three Macro parameters, φ_R, ζ_R and ϑ_R, which capture the macro effects on the power transformed realized variation. The returns equation is the same as in the non-augmented model without the direct macro effects (φ_r, ζ_r, ϑ_r=0).

In summary, the benchmark system consists of two conditional variance equations, the GARCH(1,0)-X for returns and the GARCH(1,1) for the SSR realized measure:

$$\text{HEAVY-r} : (1 - \beta_r L)\sigma_{rt}^2 = \omega_r + \alpha_{rR} L(RM_t),$$

$$\text{HEAVY-R} : (1 - \beta_R L)\sigma_{Rt}^2 = \omega_R + \alpha_{RR} L(RM_t).$$

Eq. (2) is the general formulation of the macro-augmented extension (RM_t), which incorporates leverage and power transformations to the benchmark specification (see Yfanti et al., 2022, for the relevant theoretical considerations). We also apply the Gaussian quasi-maximum likelihood estimators (QMLE) and multistep-ahead predictors already used (see Ding et al., 1993) in the APARCH framework (see, among others, He and Teräsvirta 1999, Laurent, 2004, Karanasos and Kim, 2006). We first estimate the two conditional variance equations in the general form with all the Arch, Heavy, and Asymmetry terms of eq. (2). When a parameter is insignificant, we exclude it and this results in a reduced form, statistically preferred for each volatility process. For example, in the returns and realized measure estimations, the own and cross Arch parameters (α_{rr} and α_{Rr}, respectively) are found insignificant and, are, therefore, excluded (see

[2]Glosten et. al. (1993) have introduced this type of asymmetry.

Section 5, Table 3, Panels A and B) to obtain our preferred specification for both returns and realized measures.

4 Data Description

We estimate the HEAVY framework for five stock indices returns and realized volatilities. We enrich the benchmark HEAVY model of daily returns and intra-daily realized measure with power transformations, asymmetries and macro effects as established by Karanasos and Yfanti (2020).

4.1 Volatility Measures

We source the time series data for four US and one UK stock indices from the Oxford-Man Institute's (OMI) realized library (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 02/01/2001 until 20/05/2020. We calculate the daily returns using the daily close prices, P_t^C ($r_t = ln(P_t^C) - ln(P_{t-1}^C)$). We also download the realized variance computed from the 5-minute returns, that is $RV_t = \sum x_{j,t}^2$ ($x_{j,t}^2$ is the squared 5-minute return of the j-th trade of the t-th day).

Table 1 presents the dispersion metrics for the squared returns and realized variances time series of each index over the sample period. We calculate the annualized volatility and the standard deviation of the time series. The annualized volatilities are always higher than the standard deviations. The open-to-close variation (realized variance) exhibits lower dispersion than the close-to-close yield (squared returns), as expected given that realized variance excludes the overnight noise. The annualized volatility of the realized variance is between 14% and 18%, while the squared returns range from 19% to 24%.

[Table 1 here]

We further investigate 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 the power term, δ_i. Figures 1 and 2 present the autocorrelograms of the S&P 500 index from lag 1 to 120 for $\delta_r = 1.4, 1.7, 2.0$ and $\delta_R = 1.3$, $1.6, 2.0$. The autocorrelations for $|r_t|^{1.4}$ are higher than those of $|r_t|^{\delta_r}$ for $\delta_r = 1.7, 2.0$ at every lag up to at least 120 lags. Thus, $|r_t|^{\delta_r}$ 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 3 and 4 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. We, hereby, support our motivation for enriching the Benchmark HEAVY through the APARCH framework of Ding et al. (1993) and confirm the power estimated by our econometric models, which is $\delta_r = 1.4$ for returns and $\delta_R = 1.3$ for the realized measure (see Section 5).

[Figure 1 here]

[Figure 2 here]

[Figure 3 here]

[Figure 4 here]

4.2 Macroeconomic Variables

We further study the high-frequency macro-financial linkages by adding non-negative daily macro variables to the HEAVY specification and test our research hypotheses on the economic forces driving financial volatility. We enrich the model of daily and intra-daily volatility with daily indicators of the macroeconomic conditions similar to the proxies used in the existing studies of low-frequency (monthly/quarterly) volatility determinants. Since most activity, monetary, and sentiment indices are not available at a daily frequency, we turn to other daily variables informative about the economic outlook. The EPU index is a catalytic driver of the business cycle dynamics, given its contractive impact on employment and investment (Baker et al., 2016). EPU is used here instead of the activity factors considered in the extant literature and is expected to exert the opposite effect on volatility compared to that estimated when activity variables are included. Uncertainty decreases the level of activity and high uncertainty is associated with recessions impeding subsequent recoveries. EPU also replaces macroeconomic variation and confidence indicators (Conrad and Loch, 2015). Next, we consider the daily influence from the credit channel to substitute the business and monetary conditions' effect on volatility, based on Schwert (1989), who suggested leverage, bond and interest rate volatility. Finally, given the link between commodity prices and the macroeconomy introduced by Barsky and Kilian (2004), who connected elevated oil prices with economic slowdowns, we incorporate daily commodity market indices and expect an upward response of stock volatility time series to an increase in commodity prices with distorting impact on the real economy.

In this vein, firstly, we investigate the role of uncertainty in financial volatility using the news-based EPU index (log-transformed), which incorporates both economic and policy-relevant elements of uncertainty. Secondly, for the credit conditions, we include two alternative global benchmarks of the bond market: the one-month Merrill Lynch MOVE Index (MOVE) and the Moody's triple-A Corporate Bonds Yields (M.AAA). The MOVE is the option implied volatility index of US government bonds. It is the Treasury counterpart of the VIX index for the S&P 500 and captures the sovereign credit market stance. Increased sovereign bond volatility means increased turbulence in the credit channel for governments with direct spillover (pass-through) effects on the corporate credit conditions. The M.AAA index consists of 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. Thirdly, the commodity market conditions are incorporated here with either of the two alternative global factors: the S&P Goldman Sachs Commodity Index (GSCI) and the crude oil dollar prices per barrel (West Texas Intermediate crude stream - WTI). GSCI and WTI capture the firms' production costs. Higher commodity prices lead to production and investment deterioration due to higher cost effects on corporations. The GSCI is a widely-watched global commodity markets benchmark, where most liquid commodities are included, while oil is the most important energy source across all economies. The oil is incorporated in the GSCI computation and used here as the alternative commodity regressor to the GSCI. The four credit conditions and commodities data series are retrieved from Refinitiv Workspace.

The daily macro regressors are log-transformed and included in the realized variance equation, where they are estimated to be jointly significant. Given the GARCH positivity constraints, we impose sign restrictions (positive) on the coefficients estimated for our non-negative regressors. Hence, our analysis of the macro-financial linkages is conducted on economic forces that exacerbate volatility. Figures 5-8 clearly show the comovement of realized volatility with the macro proxies. Rising uncertainty, financing costs, and commodity prices, all lead to higher volatility levels, a characteristic feature of a weaker economic stance, portrayed in the figures below, where we observe the concurrent peaks in the time series graphs around crisis episodes (see, for example, the graph peaks around the 2008 global financial crash and at the end of the sample with the pandemic crisis).

[Figure 5 here] [Figure 6 here]

[Figure 7 here] [Figure 8 here]

5 In-sample Estimation Results

Starting from Engle (2002), who proposed the GARCH-X model by adding regressors in the conditional variance equation, a large body of literature worked on the asymptotic properties of this specification with a fractionally integrated covariate (see, among others, Han and Kristensen, 2014, Han, 2015, Francq and Thieu, 2019, for the univariate case, and Ling and McAleer, 2003, Nakatani and Terasvirta, 2009, Pedersen, 2017, for the multivariate GARCH processes). For the asymmetric power HEAVY extensions, we use the Gaussian QMLE and multistep-ahead predictors of the APARCH specification (He and Teräsvirta, 1999, Laurent, 2004, Karanasos and Kim, 2006). Following Pedersen and Rahbek (2019), first, we test for conditional heteroscedasticity. Since we reject the homoscedasticity hypothesis, we perform the one-sided tests for the significance of the regressors in the GARCH equations.

We initially report the results of the benchmark HEAVY (Shephard and Sheppard, 2010), that is, the bivariate returns-realized measure system without asymmetries, power transformations, and macro effects (Table 2). The chosen equation of returns is a GARCH(1,0)-X model without the lagged squared close-to-close returns. The own Arch effect, α_{rr}, is insignificant when we add the lagged realized variance cross effect, α_{rR}. In the SSR realized variance equation, we prefer a GARCH(1,1) without the impact of returns. The preferred benchmark HEAVY formulations (after testing all alternative GARCH models of order (1,1), (1,1)-X, and (1,0)-X) are the same as in Shephard and Sheppard (2010) with similar parameter values and an identical finding that the intra-daily realized measure does all the work at moving around both conditional variances. However, this benchmark's finding, as we demonstrate below, does not apply to the macro-augmented asymmetric power system. The SBT-Sign Bias test (Engle and Ng, 1993) shows that the asymmetric effect of the returns is ignored and omitted by the benchmark estimations (p-values lower than 0.10).

[Table 2 here]

Table 3 reports the results of the 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. We apply one-sided tests because all the coefficients take non-negative values (see Pedersen and Rahbek, 2019).

In the two equations of returns and realized variance, the selected model is the double asymmetric power (DAP) one. Both power transformed variances receive the significant impact from own and cross asymmetries. We estimate the powers separately with a two-step procedure. First, we run the univariate asymmetric power models for the returns and the realized measure; the Wald tests for the power terms reject the hypotheses of $\delta_i = 1$ and $\delta_i = 2$ in most cases (available upon request). In the second step, we use the estimated powers, δ_r and δ_R, from the first step to power transform the conditional variances of both series and include them in the bivariate system. Our sequential procedure results in the fixed values of the power term, 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. The significance of both Heavy effects in the returns equation extends the specification preferred by Karanasos and Yfanti (2020), where the joint significance of α_{rR} and γ_{rR} is not included in the chosen models reported. Although α_{rr} is insignificant and excluded in all cases, the own asymmetry parameter (γ_{rr}) is significant with $\gamma_{rr} \in [0.05, 0.11]$. Therefore, we conclude that the lagged values of both powered variables drive the process of the returns' power transformed variance. The momentum, β_r, is around 0.73 to 0.90. All five indices generated very similar DAP specifications without macro effects since our realized measure equation includes the macro variables.

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 0.33 (max. value), while the own asymmetry, γ_{RR}, is between 0.03 and 0.08. The cross asymmetry Arch term is always significant with $\gamma_{Rr} \in [0.03,0.10]$. This denotes that the powered conditional variance of $\widetilde{RM}_t$ is significantly influenced by the lagged values of both powered variables: the squared negative returns and the realized measure. The momentum, β_R, is estimated to be around 0.54 to 0.77.

Finally, we test our first Hypothesis (*H1*) and find that the macro effects are significant (see Panel B). Their positive sign, as expected, confirms *H1*, that is, weak (strong) fundamentals increase (decrease) volatilities. The power transformed realized variance receives a boosting impact from higher EPU levels, $\varphi_R \in [0.01,0.03]$, in line with the results of Pastor and Veronesi (2013), who were the first to associate stock market volatilities with EPU. The uncertainty results also confirm Conrad and Loch (2015), among others, on the negative impact of confidence. Consumer confidence is the opposite sentiment to uncertainty, which is found here with the expected opposite sign. For the US indices, we use the daily US EPU index and for FTSE 100, the UK EPU instead. Regarding the credit and commodity markets, we prefer to use common global proxies for both the US and UK stock markets. Credit market conditions are better captured by the MOVE index in all cases compared to the M.AAA yields alternative. As expected, increased US treasury implied volatility raises realized volatility in stock markets ($\zeta_R \in [0.02,0.06]$) since the turbulence in the credit markets always generates significant volatility spillover effects to stock markets. This is consistent with Engle and Rangel (2008), who conclude on a positive impact of government bond interest rate volatility on stock volatility through the Spline-GARCH model. Moving to commodities, the GSCI index ($\vartheta_R \in [0.01,0.03]$) is the chosen commodity regressor across all five indices according to the information criteria minimization rule compared to the WTI alternative proxy. Crude oil coefficients are estimated positive and significant, but the commodity effect is better captured by the GSCI index (reported in Table 3), whose major component is the crude oil price. Lower commodity values depress the cost of supplies for firms. Hence, they boost productivity, investment, and, more generally, economic activity and, at the same time, reduce financial volatilities. Given that higher oil prices mostly coincide with recessions (Barsky and Kilian, 2004), the positive link between variance and commodity prices, captured by ϑ_R, confirms the negative relationship between economic activity and stock market volatility.

All in all, our estimation results show significant Heavy effects (α_{rR}, γ_{rR}, α_{RR} and γ_{RR}), Arch asymmetries (γ_{rr} and γ_{Rr}) and macro influences (φ_R, ζ_R and ϑ_R). The log-likelihood (lnL) values are higher for the m-DAP model than the lnL values of the benchmark one, showing the in-sample performance superiority of our model (Appendix A.3, Figure A.1 provides the S&P 500 standardized residuals graphs for the two models). The SBT results demonstrate that the leverage effect is not omitted since the sign coefficients are estimated insignificant, with p-values higher than 0.11. Table A.1 (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 follow the particular stepwise procedure before deciding on our final chosen model extending the HEAVY-R with powers, asymmetries, and all three macro factors. Table A.2 (Appendix A.1) presents the benchmark equation for the realized measure with macro effects for all five stock indices. Finally, Tables A.3 and A.4 (Appendix A.1) report the stepwise estimation results for our preferred benchmark and m-DAP realized variance equations of SP, where we choose MOVE and GSCI for the credit and commodity proxies (compared to Moody's AAA yields and WTI crude oil, respectively) according to the information criterion minimization rule.

Our results on macro-financial linkages are informative about the high-frequency macro drivers of the counter-cyclical financial volatility process. In line with previous studies focusing instead on the low-frequency volatility drivers or macro transmission channels (Schwert, 1989, Engle and Rangel, 2008, Pastor and Veronesi, 2013, Conrad and Loch, 2015), we identify three main transmission channels of the high-frequency macro impact on volatility in financial markets, namely:

(i) The economic sentiment channel, through which daily macro expectations, perceptions, and the subsequent feelings of economic agents are incorporated into equities. In particular, the daily loss of confidence, as proxied by economic uncertainty, exacerbates equity risk.

(ii) The credit channel, thorugh which credit conditions influence the volatility pattern. Tighter credit, proxied by the volatility of Treasury securitoe or corporate funding costs, drives the daily stock realized variance higher.

(iii) The real activity channel, through which economic recessions increase financial turbulence. In particular, higher commodity prices typically associated with activity slowdowns tend to magnify financial volatility.

[Table 3 here]

6 Out-of-sample Performance

Following our in-sample estimation of the m-DAP model, which is found superior to the benchmark specification, we examine its out-of-sample performance. We compute the multistep-ahead out-of-sample forecasts and compare the predictive accuracy of our proposed formulation with the benchmark HEAVY for the returns and the realized measure and three more standard volatility models: the GARCH(1,1) for the daily returns and the ARFIMA(1,d,1) and HAR-RV for the intra-daily realized variance.

We calculate the 1-, 5-, 10- and 22-step-ahead variance forecasts for the benchmark HEAVY, the DAP, its macro-augmented extension, and the three standard models. We choose the rolling window in-sample estimation method using 2500 observations (the initial in-sample estimation period for SP spans from 2/1/2001 until 22/12/2010) and re-estimate each model daily based on the 2500-day rolling sample. The calculated out-of-sample forecasts of each model for SP are as follows: 2362 one-step-ahead, 2358 five-step-ahead, 2353 ten-step-ahead, and 2341 twenty-two-step-ahead predicted variances. Next, we use the time series of the forecasted values and compute for each point forecast the Mean Square Error and the QLIKE loss function in comparison with the respective actual value. For each specification and forecast horizon, we calculate the average Mean Square Error (MSE) and QLIKE to create the ratio of the forecast losses for each extended HEAVY formulation (DAP and m-DAP) to the loss of the benchmark one (see also, Appendix A.2, Table A.5 for the forecast losses of all HEAVY, standard GARCH and HAR models). When the ratio is lower than one, the proposed model's forecasting performance is superior to the benchmark. The lowest ratio signifies the lowest forecast losses, that is, the model with the best predictions. Using the MSE calculations, we apply the test for the pairwise comparison of nested models (here the benchmark specification vs. the DAP extensions) introduced by Harvey, Leybourne, and Newbold (1998), HLN thereafter. The HLN forecast encompassing test is a modified version of the Diebold-Mariano test (Diebold and Mariano, 1995), which considers that the models can be nested (the DAP nests the benchmark specification). It examines whether the differences between the competing specifications' forecasts are statistically significant and whether the more general model's forecast losses are smaller than the nested model's losses (Clark and McCracken, 2001).

We implement the optimal predictor $|r_t|^{\delta}$ (as formalized in Yfanti et al., 2022, Section 3.2.3, Proposition 3) and compute the out-of-sample forecasts. The results, reported in Tables 4 and 5 for the SP index (similar results for the other four stock indices are available upon request), demonstrate the preference for our extensions compared to the benchmark specifications in all time horizons (results reported in Table A.5 also show the extended models' forecast superiority over the standard models with higher losses for GARCH, ARFIMA and HAR specifications). The m-DAP model dominates the benchmark one with the lowest MSE and QLIKE (Table 4). The HLN test shows that the AP extensions perform significantly better than the benchmarks. It rejects the null hypothesis of equal predictions in favor of the DAP's lower losses at a significance level of 5% (Table 5). Overall, the extended models perform better than the benchmarks in the short- and long-term predictions. The forecasted values are significantly closer to the actuals for the enriched specifications. The advanced in-sample estimations with asymmetries, power, and macro effects transfer their forecasting superiority to the out-of-sample computations. Our macro-informed volatility modeling framework provides reliable short-term predictions for traders, investors, portfolio and risk managers. Policymakers can further utilize our superior longer-term forecasts in scenarios of future financial volatility paths for their interventions in the financial system.

[Table 4 here]

[Table 5 here]

Market and Policy Implications

We further illustrate the equity market volatility response to the Covid-19 pandemic shock and the forecasting superiority of the HEAVY extensions during the pandemic-induced market turbulence with a real-world risk management exercise. The widely-used daily market risk metric, Value-at-Risk (VaR), denotes the potential loss of a portfolio's value, over a specific holding period, with a given confidence level (see also Karanasos et al., 2021). The VaR calculation's primary input is the one-day volatility forecast of the portfolio's risk factors. We apply the conditional variance forecasts in a long portfolio position to one S&P 500 index contract starting from 24/12/2019. We compute 100 daily VaR values from 26/12/2019 to 20/5/2020 (which mainly consists of the Coronavirus outbreak period) using the one-day variance forecasts of each returns and realized measure model. We first calculate the one-day VaR with 95% and 99% confidence levels, given the zero mean and normality assumption for the returns. Following the parametric approach to VaR calculations, we multiply the daily portfolio value with the one-day-ahead conditional volatility forecasted value (the square root of the conditional variance) and the left quantile at the confidence level of the normal distribution (the z-scores for 95% and 99% confidence levels are 1.645 and 2.326). Secondly, we compute the daily realized return of the portfolio (profit and loss). Thirdly, we conduct the backtesting exercise, comparing the realized payoff with the respective one-day VaR for the 95% and 99% confidence levels. If the realized losses exceed the respective day's VaR, we consider it an exception in backtesting, denoting that the VaR value fails to cover the losses of the particular day's portfolio valuation.

The backtesting results (Table 6: Backtesting results) show that the number of exceptions across all models is according to the selected confidence level (the 95% and 99% confidence levels allow for 5 and 1 exceptions, respectively, every 100 days) and low enough to avoid increased capital charges imposed by supervisors (in the case of the trading portfolio of a commercial bank). All exceptions are identified in March 2020, around 16/3/2020, immediately after the World Health Organization (WHO) announced that the Coronavirus outbreak is spreading at a pandemic growth rate and stock market volatilities reached their highest peak after the markets crash during the global financial crisis of 2008. More exceptions in backtesting lead to higher market risk capital requirements for banks because regulators penalize financial institutions' internal models, which fail to cover trading losses through the VaR estimates. According to the Basel traffic light approach, the capital charge for market risk rises if the backtesting exceptions are more than four in 250 daily observations and a 99% confidence level. Given that all models provide adequate coverage of the actual (realized) losses, we further scrutinize the mean and minimum VaR estimates based on the forecasts of each model (Table 6: Descriptive statistics). The VaR measure that ensures the highest loss coverage with the lowest capital charges is the VaR with the lowest minimum and highest mean values. This is provided by the realized variance formulations, for which we prefer the macro-augmented asymmetric power models. Since the capital requirement for market risk is calculated on the total trading 99% VaR (absolute value, 60-day average) and any penalty from the backtesting exercise (more than four exceptions in the 250-day period), the bank seeks the lowest possible VaR average with the highest minimum estimate in absolute terms. The macro-augmented 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 here]

Besides the risk management practice, our volatility forecasts are useful for a wide range of business operations. Portfolio managers can use the macro-informed specification to predict subsequent volatility in the minimum-variance framework of asset allocation, respecting the risk appetite of their clients. Risk-averse investors impose low volatility thresholds on their investments, while risk lovers' mandates allow higher volatilities on their portfolio positions. Future volatility predictions can also be employed in the context of a forward-looking performance evaluation through the risk-adjusted return metrics, i.e., the Treynor or the Sharpe ratios. Traders and risk practitioners focus on the volatility pattern for macro-informed trading strategies, derivatives pricing, and almost any risk and valuation task in business analytics. Investing and hedging in financial markets rely on risk factors whose forecasted volatility is the main parameter of the pricing solutions applied. Moreover, financial managers and accountants consider volatility predictions when they decide on investment projects or funding sources (the variation of expected future cash flows) and measure the fair value of financial instruments or estimate expected credit losses for financial reporting purposes. Finally, policymakers and supervisors of the financial system should use reliable volatility forecasts in designing their prudential policy responses. Regulators can rely on the macro-informed volatility forecasts of the m-DAP-HEAVY system for the proactive risk assessment of the financial system and the oversight policies for maintaining financial stability, such as the macro stress tests on financial institutions, the bank capital and risk frameworks, and the early warning systems.

7 The Uncertainty Effect on Realized Volatility

Following the extension of the benchmark HEAVY system with leverage, power, and macro effects, we delve into the impact of uncertainty on financial volatility and test our second Hypothesis (*H2*). Over the decade after 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 remarkable gap in the extant EPU literature by documenting its role within the extended HEAVY volatility modeling framework. Our analysis differs from earlier ones in the use of both daily US and UK EPU index as a determinant of daily realized volatility, with major implications for macro-informed financial investments and the actions of policymakers overseeing financial stability and managing systemic risk.

We have already observed the direct positive effect, in line with Antonakakis et al. (2013) and Pastor and Veronesi (2013), and the predictive power of daily EPU on volatility within the m-DAP framework in Sections 5 and 6. In this part of our study, 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 estimate the EPU effect in the context of the benchmark realized volatility equation augmented with the credit and commodity proxies. Table 7 reports the results of the benchmark realized volatility specification with credit (MOVE) and commodities (GSCI) for SP (similar results for the other four stock indices are available upon request). We estimate five restricted forms to observe each EPU effect separately via three interaction terms as follows: α_{RR}^{epu} is the coefficient of the EPU multiplied by the realized variance, measuring the EPU impact on the Heavy parameter (α_{RR}), ζ_R^{epu} and ϑ_R^{epu} capture the EPU effect on the credit and commodity regressors, respectively. The interaction terms are all significant and with a positive sign. We show that elevated uncertainty leads to a stronger volatility impact from credit and commodity market conditions, confirming *H2*. Given that higher uncertainty appears in economic downturns, we further elicit the connection of credit turbulence and increased commodity values during economic worsening with higher equity market volatility, a connection critically depending on the uncertainty channel. Furthermore, the arch effect of the realized variance equation, that is, the Heavy coefficient (α_{RR}), is partly attributed to EPU with α_{RR}^{epu} estimated at 0.05. EPU also exerts significant influence on the macro factors, with the credit interaction term $\zeta_R^{epu} \in [0.01,0.02]$ and the commodity interaction term ϑ_R^{epu} equal to 0.01.

[Table 7 here]

The m-DAP-HEAVY-R equation is further estimated using eight restricted forms alternatively with four EPU interaction terms: γ_{RR}^{epu} for the own Heavy asymmetry, γ_{Rr}^{epu} for the cross Arch asymmetry, ζ_R^{epu} for credit and ϑ_R^{epu} for commodities. Table 8 reports the restricted forms for SP (see also, in Table 9, Panels B and C, the EPU interaction terms estimated for all indices in the whole sample and the Covid period separately). All EPU interaction terms are positive, similar to the macro-augmented benchmark specification's results, confirming once more the amplifying EPU effect on each variable (*H2*). The own Heavy and cross Arch asymmetries are significantly and positively affected by higher uncertainty, which also magnifies the macro effects. On the one hand, within the empirical research on uncertainty, the link between uncertainty and credit conditions tightening has been explored by Alessandri and Mumtaz (2019), who relate the rising funding costs for corporations with credit market uncertainty. On the other hand, the uncertainty-commodities association has been widely investigated by Antonakakis et al. (2014) and Fang et al. (2018), among others. In particular, Antonakakis et al. (2017) analyze the oil price-equity volatility link. However, all these studies have not covered the EPU, credit, and commodities macro impact on intra-daily volatility and the EPU magnifying role through credit and production cost channels.

[Table 8 here]

To sum up, our main contribution to the EPU research consists of the novel evidence we provide on the positive association between EPU and realized volatility for both the US and the UK markets, in line with Karanasos and Yfanti (2020), who focused on European markets and the UK EPU effect only. We first demonstrate the daily EPU destabilizing impact on stock markets. Secondly, the asymmetric and Heavy effects are state-dependent, being affected by higher uncertainty. Thirdly and most interestingly, the economic interpretation of our results points out that credit market turbulence and rising commodity prices, both of which are associated with weak economic conditions, exacerbate financial volatility, and those effects are intensified by a higher EPU index.

From an economic perspective, the macro factors of stock market volatility in the m-DAP framework verify previous studies suggesting an upward volatility pattern during economic worsening. This counter-cyclical trajectory has been shown by the negative impact of economic activity indicators with quarterly or monthly frequency (Engle and Rangel, 2008). In order to explore the high-frequency domain of the macro-financial linkages, the quarterly/monthly activity proxies are replaced by daily variables of economic activity as regressors of the realized variance specification. Restricted by the non-negativity constraints, we cannot apply, among others, the daily yield curve slope (or term spread), a predictor of future GDP (Estrella and Hardouvelis, 1991) estimated significant by Conrad and Loch (2015) in the monthly context. Relying on the ample evidence of the adverse effects of uncertainty on activity (Jones and Olson, 2013, Colombo, 2013, Caggiano et al., 2017), we chose the daily EPU index to connect stock market volatility with a proxy associated with the contractive forces of economic activity. The positive sign of the EPU variable is in line with prior findings on the macroeconomic uncertainty's (Schwert, 1989) and unemployment's positive effects and the negative effect of production, GDP, and sentiment growth (Conrad and Loch, 2015). Similarly, the credit and commodities proxies linked with macro turbulence destabilize equity markets as expected by the extant empirical evidence (see, for example, Engle and Rangel, 2008, Asgharian et al., 2013, Barsky and Kilian, 2004).

Hence, in addition to contributing to the literature on realized variance modeling through the asymmetric, power, and macro-augmentation of the benchmark model applied in a broad sample with the Covid period included, we also shed light on the economic sources of financial volatility by studying the high-frequency domain of the macro-financial linkages with daily macro regressors. All three daily economic proxies that exacerbate equity volatility (higher economic uncertainty, tighter credit conditions, and increased commodity prices) are associated with economic downturns. In what follows, we focus on the macro effects during the unprecedented pandemic crisis by conducting a sensitivity analysis of the realized variance equation's parameters to quantify the Covid effect on each Heavy, Arch, and Macro coefficient.

8 The Covid-19 Effect on Macro-financial Linkages

After investigating the significant macro-financial linkages in the US and UK markets and the important role of both daily EPU indices, confirming our first two Hypotheses (*H1* and *H2*), we further explore the Covid-induced effect on equity markets and test the last Hypothesis (*H3*). The first pandemic wave immediately led to market turbulence with soaring volatilities close to the 2008 crisis peak (see the 2008 crisis structural break effect on realized variance in Karanasos and Yfanti, 2020). Markets are destabilized by the widespread worries about delayed and deficient socio-economic policies to support societies, economies, and the financial system in the US and the UK. The meteoric threat of the contagious disease has inflamed the uncertainty feelings about future economic policy choices and their potential macro impact. The ubiquitous Covid-driven uncertainty is captured by a significant increase in the level of the US and UK EPU indices.

[Figure 9 here]

[Figure 10 here]

Stock market volatility climbed to a record peak around mid-March when the World Health Organization (WHO) gave the pandemic definition to the Covid-19 spread while daily EPU levels rose sharply (see Figures 9 and 10). Against this backdrop, we estimate the Covid impact on the high-frequency macro-financial linkages by adding to the m-DAP-HEAVY-R equation three interaction terms on all Heavy, Arch, and Macro parameters (eq. (3)). The interaction terms capture the Covid-19 impact, the EPU effect in the whole sample, and, separately, in the Covid era starting from 9/1/2020 when China reported the first virus-linked death in Wuhan.

$$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R +$$

$$[\alpha_{RR} + \alpha_{RR}^{cov} D_{cov,t-1} + \alpha_{RR}^{epu} EPU_{t-1} + \alpha_{RR}^{cov\_epu} D_{cov,t-1} EPU_{t-1} +$$

$$+(\gamma_{RR}+\gamma_{RR}^{cov}D_{cov,t-1}+\gamma_{RR}^{epu}EPU_{t-1}+\gamma_{RR}^{cov\_epu}D_{cov,t-1}EPU_{t-1})s_{t-1}]L\left(RM_t\ \right)^{\frac{\delta_R}{2}}+$$

$$+\left(\gamma_{Rr}+\gamma_{Rr}^{cov}D_{cov,t-1}+\gamma_{Rr}^{epu}EPU_{t-1}+\gamma_{Rr}^{cov\_epu}D_{cov,t-1}EPU_{t-1}\right)s_{t-1}L(r_t^2)^{\frac{\delta_r}{2}}\quad+$$

$$+\left(\varphi_R+\varphi_R^{cov}D_{cov,t-1}\right)EPU_{t-1}+$$

$$+\left(\zeta_R+\zeta_R^{cov}D_{cov,t-1}+\zeta_R^{epu}EPU_{t-1}+\zeta_R^{cov\_epu}D_{cov,t-1}EPU_{t-1}\right)CR_{t-1}+$$

$$+\left(\vartheta_R+\vartheta_R^{cov}D_{cov,t-1}+\vartheta_R^{epu}EPU_{t-1}+\vartheta_R^{cov\_epu}D_{cov,t-1}EPU_{t-1}\right)CO_{t-1} \tag{3}$$

Eq. (3) incorporates the pandemic effect on realized volatility with the dummy variable, $D_{cov,t}$, defined as follows: $D_{cov,t}=0$, if $t<cov$ and $D_{cov,t}=1$, if $t\geq cov$, $cov=$ 9/1/2020, the date of the first reported death due to Covid-19. We further measure the EPU effect with the EPU interaction terms constructed by the multiplication of the EPU variable with the respective parameter of the volatility equation, similarly to Section 7 estimations (here, we report the interaction terms of the m-DAP-HEAVY-R equation for all indices). Lastly, we consider the distinct EPU effect in the Covid-era by multiplying the EPU interaction term with the Covid time dummy, $D_{cov,t}$. Table 9 summarizes the Covid and EPU effects, which are estimated by restricted forms of eq. (3) by including each Covid, EPU, and EPU under Covid effect separately for each Heavy, Arch, and Macro parameter. The Covid-crisis (Table 9, Panel A) magnifies the Arch asymmetric and all three macro effects on realized volatility (γ_{Rr}^{cov}, φ_R^{cov}, ζ_R^{cov}, ϑ_R^{cov}) while the distinct Heavy effects during the pandemic are mostly insignificant (α_{RR}^{cov}, γ_{RR}^{cov}). Similarly to the analysis in Section 7, the EPU effect, reported for all five indices here, is always positive and highly significant in all cases (γ_{RR}^{epu}, γ_{Rr}^{epu}, ζ_R^{epu}, ϑ_R^{epu}), apart from the Heavy parameter, α_{RR}^{epu}, where in three out of the five indices the uncertainty impact is insignificant (Table 9, Panel B). Furthermore, rising EPU levels during the pandemic remarkably increase the effect of negative squared returns, credit and commodity proxies on realized variance ($\gamma_{Rr}^{cov\_epu}$, $\zeta_R^{cov\_epu}$, $\vartheta_R^{cov\_epu}$) while the Heavy coefficients ($\alpha_{RR}^{cov\_epu}$, $\gamma_{RR}^{cov\_epu}$) are mostly unaffected (Table 9, Panel C). Our results show that the market turbulence caused by Covid-19 is striking. We find a significant inflating effect on the exacerbating impact of the Arch asymmetry and Macro parameters, confirming *H3*. We also provide sound evidence of the pandemic's destabilizing impact through the uncertainty channel on financial volatilities, given the significant EPU effect during the disease spread.

[Table 9 here]

9 Conclusions

We have applied the HEAVY framework in US and UK equity market volatility modeling enriched with asymmetric, power, and macro features for a sample covering the Covid-induced crisis in financial markets. Our in-sample estimation results favor the most general double asymmetric power specification for the variance of returns and realized measure, where both powered transformed variables and leverage effects are significant in both equations of the bivariate system, in line with Karanasos and Yfanti (2020). The macro-extension of the asymmetric power process produces a specification that clearly outperforms its rivals, and that can be used for the purposes of portfolio and risk management. In particular, we show that it has a better out-of-sample forecasting performance over both short- and long-term horizons during the pandemic crash. Finally, our macro-analysis reveals that distinct features of economic worsening, such as higher macro uncertainty, commodity prices, and credit conditions tightening, raise equity volatilities, while

EPU further intensifies the Heavy, Arch and, macro effects on the realized measure, particularly during the recent period of the Covid-19 outbreak.

Our insights on the link between high- and low-frequency volatility measures and daily macro factors during the current health crisis project important implications for policy and market practitioners and suggest possible avenues for future research to extend the HEAVY model further. Our framework can be used by both policymakers and market experts to analyze and predict financial volatility trajectories even in crisis periods with the aim of designing policies to preserve financial stability and deciding on asset allocation, hedging strategies, investment projects, funding sources, and capital risk buffers (for bank managers, in particular). The research potential of the macro-augmented HEAVY system for financial volatility is still large. Therefore, future research could extend the analysis to commodities and other asset classes (e.g., foreign exchange rates, bonds, cryptocurrencies) using, in each case, appropriate macro proxies for volatility. Finally, 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 on the uncertainty channel repercussions.

A APPENDIX

A.1 Realized Measure Equation Analysis

[Table A.1 here]

[Table A.2 here]

[Table A.3 here]

[Table A.4 here]

A.2 Forecast Losses

[Table A.5 here]

A.3 S&P 500 Residuals Graphs

[Figure A.1 here]

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Table 1: Dispersion measures for squared returns and realized variance.

	Sample period			r_t^2		RV_t	
Index	Start date	End date	Obs.	Avol	sd	Avol	sd
SP	02/01/2001	20/05/2020	4862	0.197	0.057	0.167	0.027
DJ	02/01/2001	20/05/2020	4859	0.189	0.057	0.169	0.029
NASDAQ	02/01/2001	20/05/2020	4861	0.235	0.068	0.166	0.022
RUSSELL	02/01/2001	20/05/2020	4859	0.244	0.076	0.141	0.018
FTSE	02/01/2001	20/05/2020	4887	0.186	0.043	0.176	0.031

Notes:

The table reports the dispersion measures of the squared returns and realized variance time series data in the whole sample period. Avol and sd denote the annualized volatility and standard deviation, respectively.

Table 2: The Benchmark HEAVY model.

	SP	DJ	NASDAQ	RUSSELL	FTSE
	Panel A. Stock Returns: HEAVY- r				
	$(1-\beta_r L)\sigma_{rt}^2 = \omega_r + \alpha_{rR} L(RM_t)$				
β_r	**0.59**	0.62	0.63	<u>0.67</u>	0.63
	(11.69)***	(14.22)***	(11.45)***	(15.93)***	(13.71)***
α_{rR}	0.55	0.45	0.70	<u>0.78</u>	**0.40**
	(7.49)***	(7.85)***	(6.67)***	(7.49)***	(7.43)***
Q_{12}	17.29	13.05	10.91	15.25	4.60
	[0.14]	[0.37]	[0.54]	[0.23]	[0.97]
SBT	2.81	1.73	1.97	1.69	2.26
	[0.01]	[0.08]	[0.05]	[0.09]	[0.02]
lnL	-6357.31	-6208.70	-7464.03	-7979.69	-6497.69
	Panel B. Realized Measure: HEAVY- R				
	$(1-\beta_R L)\sigma_{Rt}^2 = \omega_R + \alpha_{RR} L(RM_t)$				
β_R	0.52	0.56	**0.44**	0.53	<u>0.62</u>
	(14.21)***	(14.73)***	(13.25)***	(15.87)***	(16.79)***
α_{RR}	0.49	0.44	<u>0.53</u>	0.42	**0.38**
	(11.97)***	(9.08)***	(15.40)***	(13.48)***	(9.52)***
Q_{12}	10.79	13.76	6.65	14.96	10.23
	[0.55]	[0.32]	[0.88]	[0.24]	[0.60]
SBT	4.82	3.61	3.76	3.10	2.64
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
lnL	-6026.19	-5754.72	-5981.74	-5197.18	-6257.32

Notes:

The table presents the bivariate benchmark HEAVY system. The numbers in square brackets are p-values. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. 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. Bold (underlined) numbers indicate minimum (maximum) values across the five indices.

Table 3: The m-DAP-HEAVY model.

	SP	DJ	NASDAQ	RUSSELL	FTSE
Panel A. Stock Returns: m-DAP-HEAVY- r					
$(1-\beta_r L)(\sigma_{rt}^2)^{\frac{\delta_r}{2}} = \omega_r + (\alpha_{rr} + \gamma_{rr} s_{t-1}) L(r_t^2)^{\frac{\delta_r}{2}} + (\alpha_{rR} + \gamma_{rR} s_{t-1}) L(RM_t\ )^{\frac{\delta_R}{2}}$					
β_r	0.75	0.78	**0.73**	<u>0.90</u>	0.82
	(26.64)***	(36.42)***	(19.60)***	(82.14)***	(31.93)***
α_{rR}	0.14	0.09	<u>0.27</u>		**0.07**
	(4.34)***	(3.87)***	(4.62)***		(2.67)***
γ_{rr}	**0.05**	0.09	**0.05**	<u>0.11</u>	<u>0.11</u>
	(2.50)***	(5.28)***	(2.57)***	(11.11)***	(6.77)***
γ_{rR}	<u>0.19</u>	0.12	0.18	**0.08**	0.09
	(6.18)***	(4.92)***	(4.45)***	(3.32)***	(4.20)***
Q_{12}	12.20	14.50	8.99	14.17	5.51
	[0.27]	[0.27]	[0.70]	[0.17]	[0.94]
SBT	1.51	1.06	1.13	0.23	1.56
	[0.13]	[0.29]	[0.26]	[0.82]	[0.12]
lnL	-5980.38	-5865.44	-6888.80	-7121.48	-6142.30
Panel B. Realized Measure: m-DAP-HEAVY- R					
$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_i + (\alpha_{Rr} + \gamma_{Rr} s_{t-1}) L(r_t^2)^{\frac{\delta_r}{2}} + (\alpha_{RR} + \gamma_{RR} s_{t-1}) L\big(RM_t\ \big)^{\frac{\delta_R}{2}} + +\varphi_R EPU_{t-1} + \zeta_R CR_{t-1} + \vartheta_R CO_{t-1}$					
β_R	0.64	0.69	**0.54**	0.64	<u>0.77</u>
	(27.86)***	(33.89)***	(22.00)***	(27.18)***	(38.15)***
α_{RR}	0.22	0.18	<u>0.33</u>	0.23	**0.13**
	(10.82)***	(10.40)***	(15.41)***	(11.77)***	(5.97)***
γ_{RR}	0.07	0.07	**0.03**	<u>0.08</u>	0.05
	(6.05)***	(5.91)***	(2.38)**	(0.08)***	(3.30)***
γ_{Rr}	0.09	<u>0.10</u>	0.07	**0.03**	0.09
	(9.57)***	(8.60)***	(11.35)***	(8.22)***	(11.14)***
φ_R	<u>0.03</u>	0.02	0.02	0.02	**0.01**
	(4.13)***	(3.11)***	(2.19)**	(2.73)***	(3.16)***
ζ_R	<u>0.06</u>	0.05	0.05	**0.02**	0.05
	(4.14)***	(4.26)***	(3.30)***	(2.58)***	(4.81)***
	MOVE	*MOVE*	*MOVE*	*MOVE*	*MOVE*
ϑ_R	<u>0.03</u>	<u>0.03</u>	**0.01**	0.02	**0.01**
	(4.78)***	(4.50)***	(2.30)**	(2.92)***	(2.08)**
	GSCI	*GSCI*	*GSCI*	*GSCI*	*GSCI*
Q_{12}	14.04	14.57	6.50	15.46	11.52
	[0.30]	[0.27]	[0.89]	[0.22]	[0.49]
SBT	0.44	0.26	0.12	1.21	0.82
	[0.66]	[0.79]	[0.91]	[0.23]	[0.41]
lnL	-5934.08	-5670.01	-5879.11	-5039.12	-5800.00
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:

The table reports the estimation of the m-DAP-HEAVY model. The numbers in square brackets are p-values. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. 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. Bold (underlined) numbers indicate minimum (maximum) values across the five indices.

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

	MSE				QLIKE			
Specifications↓ m-steps →	1	5	10	22	1	5	10	22
Panel A: Stock Returns (HEAVY-r)								
Benchmark	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
m-DAP	**0.789**	**0.816**	**0.867**	**0.933**	**0.741**	**0.782**	**0.854**	**0.890**
Panel B: Realized Measure (HEAVY-R)								
Benchmark	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DAP	0.761	0.819	0.873	0.879	0.770	0.761	0.831	0.922
m-DAP with EPU only	0.743	0.802	0.851	0.881	0.724	0.740	0.806	0.866
m-DAP	**0.656**	**0.781**	**0.844**	**0.863**	**0.691**	**0.738**	**0.795**	**0.859**

Notes:

The table reports the MSE and QLIKE ratios of the SP conditional variance forecasts from the extended compared to the benchmark models. Bold numbers indicate minimum values across the different specifications.

Table 5: HLN Forecast encompassing test results for SP (p-values).

Specifications↓ m-steps →	1	5	10	22
Panel A: Stock Returns (HEAVY-r)				
Benchmark vs m-DAP	0.005	0.023	0.036	0.052
Panel B: Realized Measure (HEAVY-R)				
Benchmark vs DAP	0.027	0.029	0.041	0.040
Benchmark vs m-DAP with EPU only	0.025	0.028	0.040	0.044
Benchmark vs m-DAP	0.003	0.022	0.030	0.050

Notes:

The numbers reported are p-values of the HLN (1998) test of the null hypothesis for equal forecasting performance against the one-sided alternative that the extended outperforms the nested specification for SP.

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

	Backtesting results No. of Exceptions		Descriptive statistics 99% VaR		95% VaR	
Specifications	99% VaR	95% VaR	Mean	Min.	Mean	Min.
Panel A: Stock Returns (HEAVY-r)						
GARCH(1,1)	1	2	-93.23	-157.88	-65.67	-112.89
Benchmark	1	2	-80.12	-149.76	-57.68	-102.39
m-DAP	1	2	-76.34	-133.54	-51.55	-95.41
Panel B: Realized Measure (HEAVY-R)						
ARFIMA(1,d,1)	1	2	-85.26	-134.98	-60.71	-93.77
HAR-RV	1	2	-89.51	-131.75	-63.62	-90.11
Benchmark	1	2	-70.34	-120.32	-50.19	-83.26
DAP	1	2	-76.23	-122.83	-53.88	-84.34
m-DAP with EPU	1	2	**-75.66**	**-129.31**	-53.67	-89.46
m-DAP with EPU, Credit & Commodities	1	2	**-72.14**	**-136.69**	-50.16	-94.99

Notes:
The table reports the VaR backtesting exercise and the descriptive statistics of the portfolio VaR for SP. 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.

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

$$1-\beta_R L)\sigma_{Rt}^2 = \omega_R + (\alpha_{RR} + \alpha_{RR}^{epu} EPU_{t-1})L(RM_t) + +(\zeta_R + \zeta_R^{epu} EPU_{t-1})CR_{t-1} + (\vartheta_R + \vartheta_R^{epu} EPU_{t-1})CO_{t-1}$$

	(1)	(2)	(3)	(4)	(5)
β_R	0.47	0.48	0.48	0.49	0.48
	(12.91)***	(13.03)***	(12.86)***	(13.54)***	(12.87)***
α_{RR}	0.42	0.50	0.49	0.49	0.49
	(9.26)***	(12.64)***	(12.51)***	(12.15)***	(12.49)***
α_{RR}^{epu}	0.05				
	(2.89)***				
ζ_R	0.06	0.07	0.04		0.07
	(2.88)***	(3.40)***	(1.83)*		(3.31)***
	MOVE	*MOVE*	*MOVE*		*MOVE*
ζ_R^{epu}		0.01	0.02		
		(2.64)***	(3.20)***		
		MOVE	*MOVE*		
ϑ_R	0.02		0.03	0.03	0.02
	(1.72)*		(2.84)***	(2.97)***	(1.70)*
	GSCI		*GSCI*	*GSCI*	*GSCI*
ϑ_R^{epu}				0.01	0.01
				(3.30)***	(3.27)***
				GSCI	*GSCI*

Notes:
The table reports the benchmark HEAVY-R equation for SP extended with the indirect EPU effect. Superscripts indicate the EPU effect on the respective parameter. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table 8: The m-DAP-HEAVY-R equation for SP with the EPU effect on Heavy, Arch and Macro parameters.

$$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + [\alpha_{RR} + (\gamma_{RR} + \gamma_{RR}^{epu} EPU_{t-1}) s_{t-1}] L(RM_t\ )^{\frac{\delta_R}{2}} +$$
$$+(\gamma_{Rr} + \gamma_{Rr}^{epu} EPU_{t-1}) s_{t-1} L(r_t^2)^{\frac{\delta_r}{2}} \ +(\zeta_R + \zeta_R^{epu} EPU_{t-1}) CR_{t-1} +$$
$$+(\vartheta_R + \vartheta_R^{epu} EPU_{t-1}) CO_{t-1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_R	0.63	0.62	0.62	0.64	0.63	0.64	0.65	0.64
	(28.33)***	(27.19)***	(27.24)***	(28.20)***	(28.16)***	(27.79)***	(29.23)***	(27.83)***
α_{RR}	0.23	0.23	0.23	0.15	0.23	0.22	0.22	0.22
	(11.39)***	(11.51)***	(11.50)***	(6.15)***	(11.64)***	(10.80)***	(11.16)***	(10.80)***
γ_{RR}				0.06	0.07	0.07	0.07	0.07
				(6.40)***	(5.84)***	(6.06)***	(5.86)***	(6.04)***
γ_{RR}^{epu}	0.04	0.04	0.04	0.04				
	(6.04)***	(5.69)***	(5.69)***	(5.86)***				
γ_{Rr}				0.09	0.09	0.09	0.09	0.09
				(9.33)***	(9.30)***	(9.57)***	(9.48)***	(9.56)***
γ_{Rr}^{epu}	0.05	0.05	0.05					
	(9.06)***	(9.13)***	(9.13)***					
ζ_R	0.06	0.05	0.06	0.06	0.06	0.03		0.06
	(4.50)***	(3.15)***	(4.42)***	(4.39)***	(4.10)***	(1.90)**		(4.13)***
	MOVE	*MOVE*	*MOVE*	*MOVE*	*MOVE*	*MOVE*		*MOVE*
ζ_R^{epu}		0.01			0.02	0.02		
		(2.24)**			(3.04)***	(4.21)***		
		MOVE			*MOVE*	*MOVE*		
ϑ_R	0.03	0.03	0.03	0.03		0.03	0.03	0.02
	(4.13)***	(4.66)***	(3.78)***	(3.98)***		(4.81)***	(4.46)***	(2.99)***
	GSCI	*GSCI*	*GSCI*	*GSCI*		*GSCI*	*GSCI*	*GSCI*
ϑ_R^{epu}			0.004				0.02	0.02
			(2.24)**				(4.34)***	(4.19)***
			GSCI				*GSCI*	*GSCI*
δ_r	1.40							
δ_R	1.30							

Notes:
The table reports the m-DAP-HEAVY-R equation for SP extended with the indirect EPU effect. Superscripts indicate the EPU effect on the respective parameter. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table 9: The Covid-19 and EPU effect on Heavy, Arch and Macro parameters in the m-DAP-HEAVY-R equation (eq. (3))

	SP	DJ	NASDAQ	RUSSELL	FTSE
Panel A: The Covid-19 effect					
α_{RR}^{cov}	0.02	0.01	0.04	0.03	0.02
	(0.77)	(0.61)	(1.66)*	(1.85)*	(1.01)
γ_{RR}^{cov}	0.03	0.03	0.04	0.07	0.05
	(0.72)	(0.99)	(0.88)	(1.82)*	(1.21)
γ_{Rr}^{cov}	0.05	0.05	0.06	0.03	0.07
	(2.24)**	(2.26)**	(2.37)**	(2.50)***	(2.09)**
φ_{R}^{cov}	0.01	0.01	0.02	0.01	0.01
	(1.65)*	(1.63)*	(1.78)*	(1.73)*	(1.62)*
ζ_{R}^{cov}	0.01	0.01	0.02	0.01	0.02
	(1.66)*	(1.71)*	(1.79)*	(1.66)*	(1.69)*
	MOVE	*MOVE*	*MOVE*	*MOVE*	*MOVE*
ϑ_{R}^{cov}	0.01	0.01	0.01	0.01	0.01
	(1.69)*	(1.76)*	(1.74)*	(1.63)*	(1.69)*
	GSCI	*GSCI*	*GSCI*	*GSCI*	*GSCI*
Panel B: The EPU effect in the whole sample					
α_{RR}^{epu}	0.02	0.01	0.04	0.05	0.02
	(0.88)	(0.51)	(1.78)*	(2.42)**	(0.77)
γ_{RR}^{epu}	0.04	0.04	0.02	0.04	0.02
	(5.86)***	(5.71)***	(2.59)***	(6.88)***	(3.03)***
γ_{Rr}^{epu}	0.05	0.05	0.03	0.02	0.04
	(9.22)***	(8.12)***	(10.90)***	(8.35)***	(10.98)***
ζ_{R}^{epu}	0.02	0.03	0.03	0.01	0.02
	(3.04)***	(4.37)***	(3.43)***	(2.39)**	(5.17)***
	MOVE	*MOVE*	*MOVE*	*MOVE*	*MOVE*
ϑ_{R}^{epu}	0.02	0.02	0.01	0.01	0.001
	(4.34)***	(4.46)***	(1.64)*	(2.85)***	(1.63)*
	GSCI	*GSCI*	*GSCI*	*GSCI*	*GSCI*
Panel C: The EPU effect in the Covid-19 period					
$\alpha_{RR}^{cov\_epu}$	0.004	0.002	0.01	0.01	0.004
	(0.47)	(0.33)	(1.63)*	(1.77)*	(0.62)***
$\gamma_{RR}^{cov\_epu}$	0.01	0.01	0.01	0.03	0.01
	(0.42)	(0.66)	(0.67)	(1.71)*	(1.02)
$\gamma_{Rr}^{cov\_epu}$	0.01	0.02	0.02	0.02	0.03
	(1.66)*	(2.05)**	(2.20)**	(3.62)***	(2.01)**
$\zeta_{R}^{cov\_epu}$	0.01	0.004	0.01	0.01	0.01
	(1.66)*	(1.69)*	(1.82)*	(1.71)*	(1.67)*
	MOVE	*MOVE*	*MOVE*	*MOVE*	*MOVE*
$\vartheta_{R}^{cov\_epu}$	0.003	0.002	0.01	0.003	0.004
	(1.70)*	(1.69)*	(1.81)*	(1.66)*	(1.64)*
	GSCI	*GSCI*	*GSCI*	*GSCI*	*GSCI*

Notes:
The table reports the pandemic and EPU effect estimated in the m-DAP-HEAVY-R equation. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. Superscripts indicate the Covid-19 effect (^{cov}), the EPU effect in the whole sample (^{epu}), and the EPU effect in the Covid-19 period ($^{cov\_epu}$).

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

	SP	DJ	NASDAQ	RUSSELL	FTSE
Panel A. Realized Measure: DAP-HEAVY- R					
$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{RR} + \gamma_{RR} s_{t-1}) L(RM_t\ )^{\frac{\delta_R}{2}} + +\gamma_{Rr} s_{t-1} L(r_t^2)^{\frac{\delta_r}{2}}$					
β_R	0.65	0.70	**0.56**	0.64	0.77
	(30.82)***	(38.01)***	(23.61)***	(27.72)***	(40.95)***
α_{RR}	0.24	0.20	0.33	0.24	**0.14**
	(12.34)***	(12.00)***	(15.79)***	(11.91)***	(6.71)***
γ_{RR}	0.07	0.07	**0.02**	0.08	0.05
	(5.46)***	(5.86)***	(2.17)**	(7.00)***	(3.22)***
γ_{Rr}	0.08	0.09	0.07	**0.03**	0.08
	(9.01)***	(7.93)***	(11.19)***	(7.81)***	(10.62)***
lnL	-5947.31	-5723.10	-5927.50	-5061.56	-5839.15
Panel B. Realized Measure: m-DAP-HEAVY- R with EPU only					
$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + (\alpha_{RR} + \gamma_{RR} s_{t-1}) L(RM_t\ )^{\frac{\delta_R}{2}} + +\gamma_{Rr} s_{t-1} L(r_t^2)^{\frac{\delta_r}{2}} + \varphi_R EPU_{t-1}$					
β_R	0.65	0.69	**0.55**	0.63	0.77
	(30.28)***	(37.10)***	(22.98)***	(26.95)***	(40.29)***
α_{RR}	0.24	0.20	0.34	0.24	**0.14**
	(12.44)***	(12.03)***	(15.84)***	(11.96)***	(6.78)***
γ_{RR}	0.07	0.07	**0.02**	0.08	0.04
	(5.45)***	(5.85)***	(2.19)**	(7.05)***	(3.32)***
γ_{Rr}	0.09	0.09	0.07	**0.03**	0.08
	(9.10)***	(7.96)***	(11.24)***	(7.75)***	(10.63)***
φ_R	0.02	**0.01**	**0.01**	**0.01**	**0.01**
	(4.02)***	(2.04)**	(1.97)**	(2.00)**	(2.26)**
lnL	-5937.55	-5700.21	-5920.07	-5055.11	-5831.88
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:

The table reports the estimation of the (m-)DAP-HEAVY-R equation without and with the direct EPU effect. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. lnL denotes the log-likelihood value for each specification. Bold (underlined) numbers indicate minimum (maximum) values across the five indices.

Table A.2: The Benchmark HEAVY-R equation with EPU, Credit & Commodities.

$$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + \alpha_{RR} L(RM_t) + \\ +\varphi_R EPU_{t-1} + \zeta_R CR_{t-1} + \vartheta_R CO_{t-1}$$

	SP	DJ	NASDAQ	RUSSELL	FTSE
β_R	0.48	0.52	**0.42**	0.52	<u>0.60</u>
	(12.89)***	(12.94)***	(12.24)***	(15.32)***	(14.88)***
α_{RR}	0.49	0.45	<u>0.54</u>	0.43	**0.38**
	(12.49)***	(10.01)***	(15.56)***	(13.64)***	(9.42)***
φ_R	<u>0.03</u>	**0.02**	**0.02**	**0.02**	**0.02**
	(3.14)***	(2.46)***	(1.73)*	(2.15)**	(1.66)*
ζ_R	<u>0.07</u>	<u>0.07</u>	0.06	**0.05**	<u>0.07</u>
	(3.32)***	(3.09)***	(2.24)**	(2.96)***	(2.32)**
	MOVE	*MOVE*	*MOVE*	*MOVE*	*MOVE*
ϑ_R	0.03	<u>0.04</u>	**0.02**	0.03	
	(2.80)***	(2.75)***	(1.65)*	(2.24)**	
	GSCI	*GSCI*	*GSCI*	*GSCI*	
lnL	-6010.34	-5746.31	-5973.71	-5176.34	-6219.94

Notes:
The table reports the Benchmark HEAVY-R equation with Macro effects. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. lnL denotes the log-likelihood value for each specification. Bold (underlined) numbers indicate minimum (maximum) values across the five indices.

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

$$(1-\beta_R L)(\sigma_{Rt}^2)^{\frac{\delta_R}{2}} = \omega_R + \alpha_{RR} L(RM_t) + \varphi_R EPU_{t-1} + \zeta_R CR_{t-1} + \vartheta_R CO_{t-1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_R	0.51	0.48	0.50	0.50	0.51	0.48	0.48	0.50	0.50
	(14.07)***	(13.06)***	(13.56)***	(13.45)***	(14.12)***	(12.89)***	(13.04)***	(13.54)***	(13.49)***
α_{RR}	0.49	0.50	0.49	0.49	0.49	0.49	0.50	0.49	0.49
	(12.10)***	(12.63)***	(12.15)***	(12.01)***	(12.13)***	(12.49)***	(12.69)***	(12.14)***	(12.04)***
φ_R	0.02	0.02	0.03	0.03	0.02	<u>0.03</u>	0.02	0.03	0.03
	(2.28)**	(2.59)***	(3.18)***	(2.97)***	(1.99)**	(3.14)***	(2.35)**	(3.19)***	(2.72)***
ζ_R		0.10		0.07		<u>0.07</u>	0.10	0.02	0.07
		(4.41)***		(2.77)***		(3.32)***	(4.63)***	(1.80)*	(2.69)***
		MOVE		*AAA*		*MOVE*	*MOVE*	*AAA*	*AAA*
ϑ_R			0.05		0.02	0.03	0.03	0.05	0.02
			(4.15)***		(1.88)*	(2.80)***	(2.53)***	(4.08)***	(1.68)*
			GSCI		*WTI*	*GSCI*	*WTI*	*GSCI*	*WTI*
AIC	2.31610	2.31502	2.31532	2.31587	2.31610	2.31496	2.31506	2.31573	2.31612

Notes:
The table reports the stepwise estimation of the Benchmark HEAVY-R equation with Macro effects for SP. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. AIC denotes the Akaike Information criterion.

Table A.4: The m-DAP-HEAVY-R equation for SP with EPU, Credit & Commodities (stepwise procedure).

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_R	0.65	0.63	0.65	0.65	0.65	0.64	0.64	0.65	0.65
	(30.28)***	(28.19)***	(29.26)***	(29.13)***	(30.07)***	(27.86)***	(27.95)***	(28.91)***	(28.95)***
α_{RR}	0.24	0.23	0.22	0.22	0.24	0.22	0.23	0.22	0.22
	(12.44)***	(11.64)***	(11.18)***	(11.31)***	(12.30)***	(10.82)***	(11.31)***	(10.97)***	(11.14)***
γ_{RR}	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
	(5.45)***	(5.83)***	(5.87)***	(5.85)***	(5.43)***	(6.05)***	(5.84)***	(5.94)***	(5.85)***
γ_{Rr}	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
	(9.10)***	(9.29)***	(9.48)***	(9.36)***	(9.17)***	(9.57)***	(9.44)***	(9.49)***	(9.45)***
φ_R	0.02	0.02	0.03	0.03	0.02	0.03	0.02	0.03	0.03
	(4.02)***	(2.95)***	(4.26)***	(4.39)***	(2.37)**	(4.13)***	(2.57)***	(4.57)***	(4.10)***
ζ_R		0.07		0.08		0.06	0.08	0.04	0.08
		(5.49)***		(5.38)***		(4.14)***	(5.84)***	(2.28)**	(5.45)***
		MOVE		*AAA*		*MOVE*	*MOVE*	*AAA*	*AAA*
ϑ_R			0.04		0.01	0.03	0.02	0.03	0.02
			(6.14)***		(1.89)*	(4.78)***	(3.13)***	(3.33)***	(2.17)**
			GSCI		*WTI*	*GSCI*	*WTI*	*GSCI*	*WTI*
δ_r					1.40				
δ_R					1.30				
AIC	2.30564	2.30531	2.30527	2.30537	2.30599	2.30521	2.30553	2.30558	2.30570

Notes:

The table reports the stepwise estimation of the m-DAP-HEAVY-R equation for SP. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. AIC denotes the Akaike Information criterion.

Table A.5: Mean Square Error (MSE) of m-step-ahead out-of-sample forecasts for SP

Specifications↓	m-steps →	1	5	10	22
Panel A: Stock Returns					
GARCH(1,1)		1.99177	2.83313	3.22341	6.35942
Benchmark HEAVY-r		1.86670	2.42979	2.62279	5.75513
m-DAP-HEAVY-r		**1.47283**	**1.98270**	**2.27396**	**5.36954**
Panel B: Realized Measure					
ARFIMA(1,d,1)		1.27116	2.01750	1.44358	1.30326
HAR-RV		1.26015	1.99137	1.41074	1.38670
Benchmark HEAVY-R		1.22345	1.86633	1.26297	1.09794
DAP-HEAVY-R		0.93105	1.52852	1.10257	0.96509
m-DAP-HEAVY-R with EPU only		0.90902	1.49680	1.07479	0.96729
m-DAP-HEAVY-R		**0.80258**	**1.45760**	**1.06595**	**0.94752**

Notes:

The table reports the Mean Square Error of the SP conditional variance forecasts. Bold numbers indicate minimum values across the different specifications.

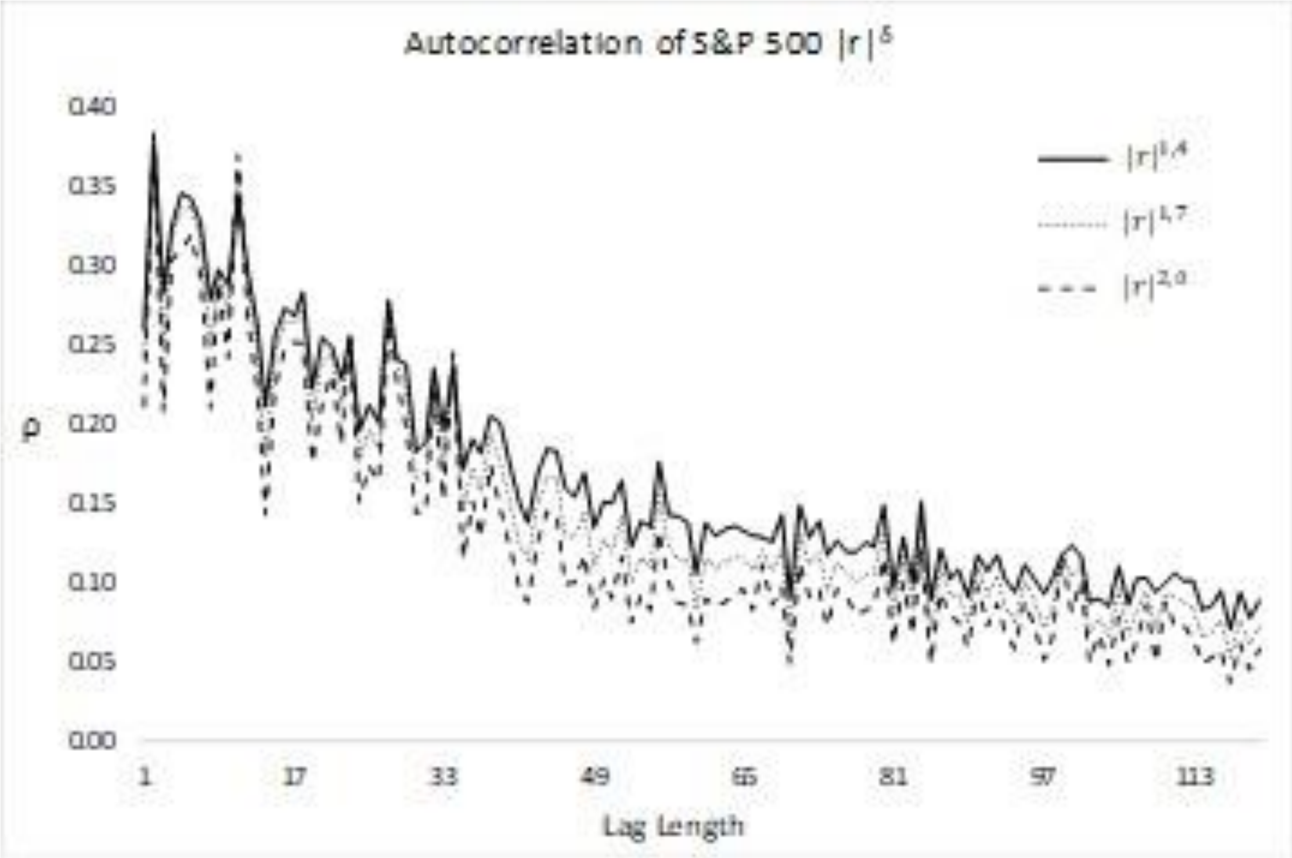

Figure 1. Autocorrelation of S&P 500 $|r_t|^{\delta_r}$ for $\delta_r = 1.4, 1.7, 2.0$

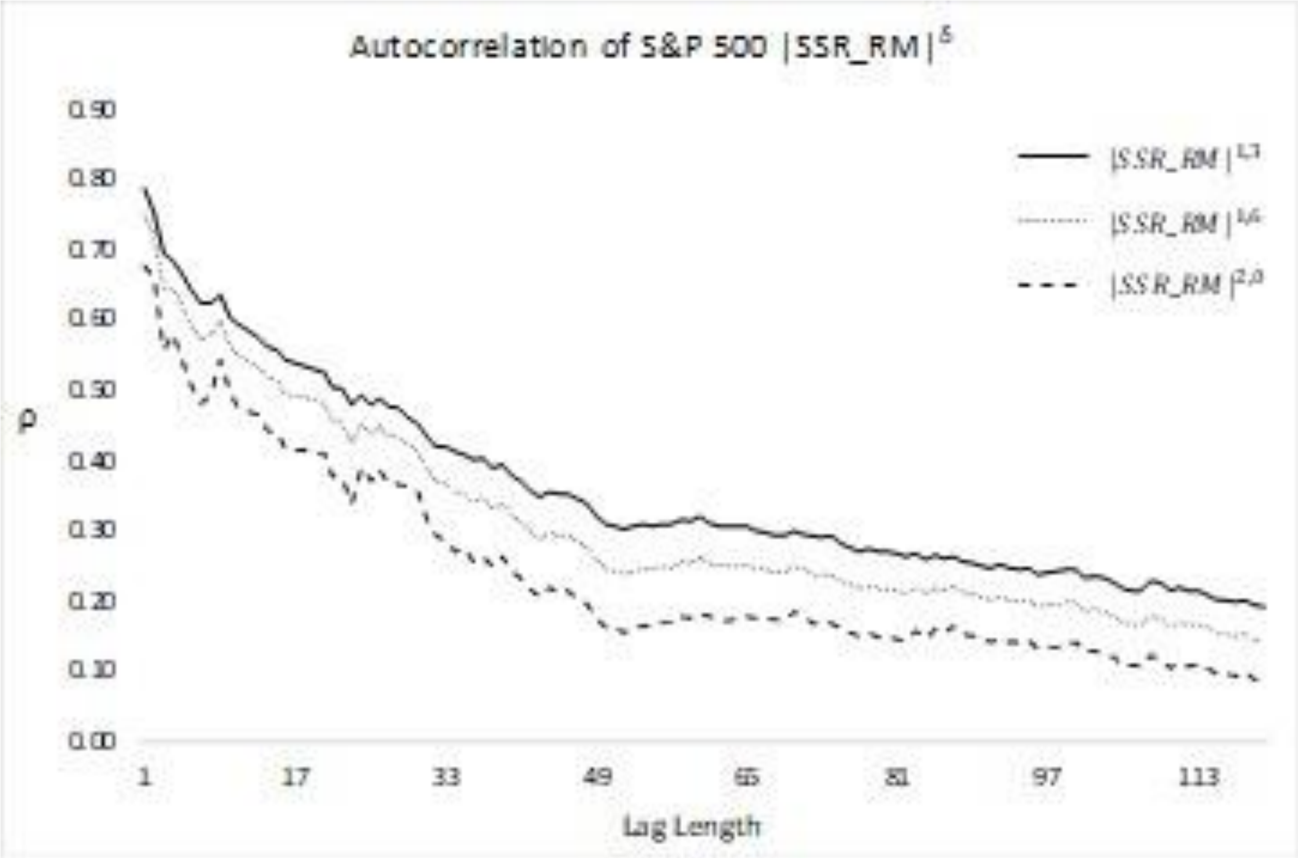

Figure 2. Autocorrelation of S&P 500 $|SSR\_RM_t|^{\delta_R}$ for $\delta_R = 1.3,\ 1.6, 2.0$

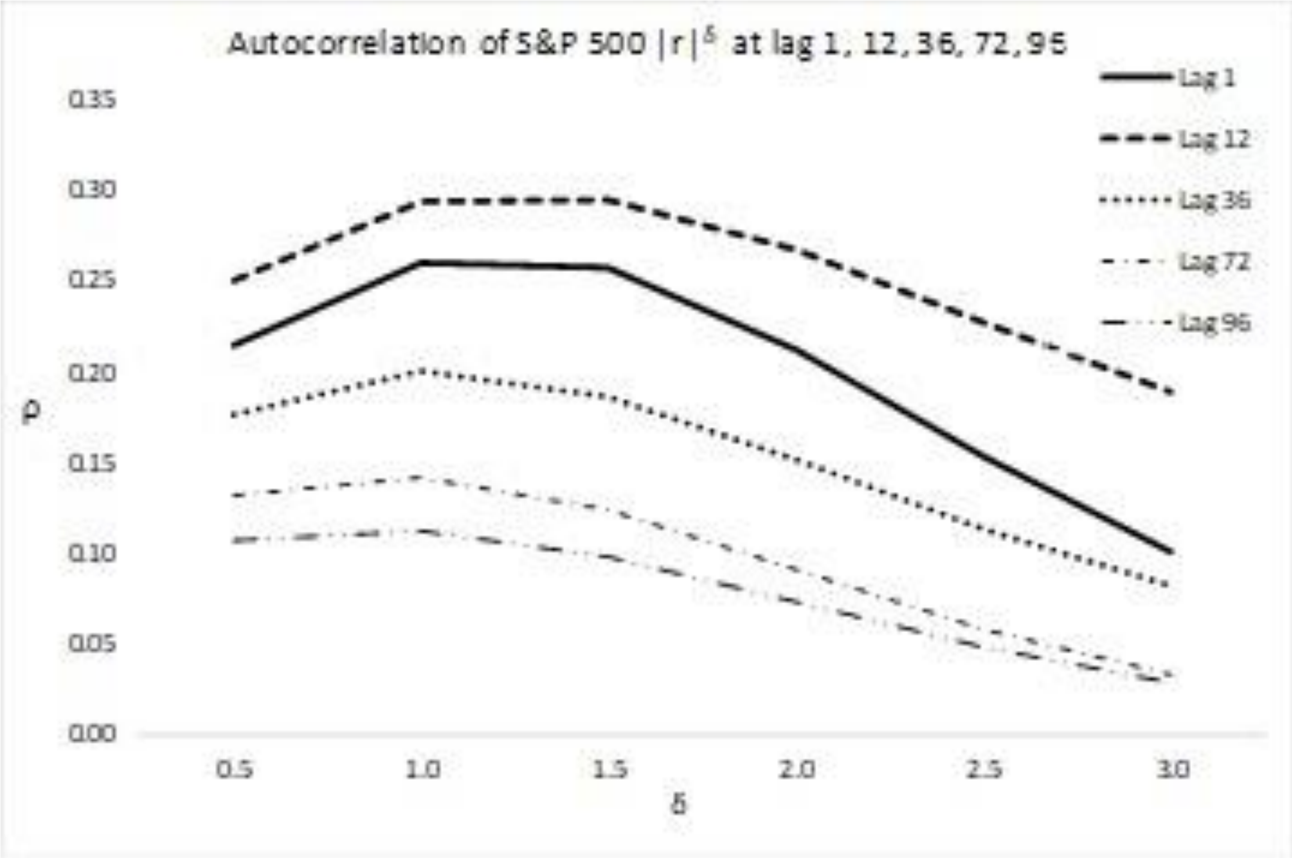

Figure 3. Autocorrelation of S&P 500 $|r_t|^{\delta_r}$ at lags 1, 12, 36, 72, 96

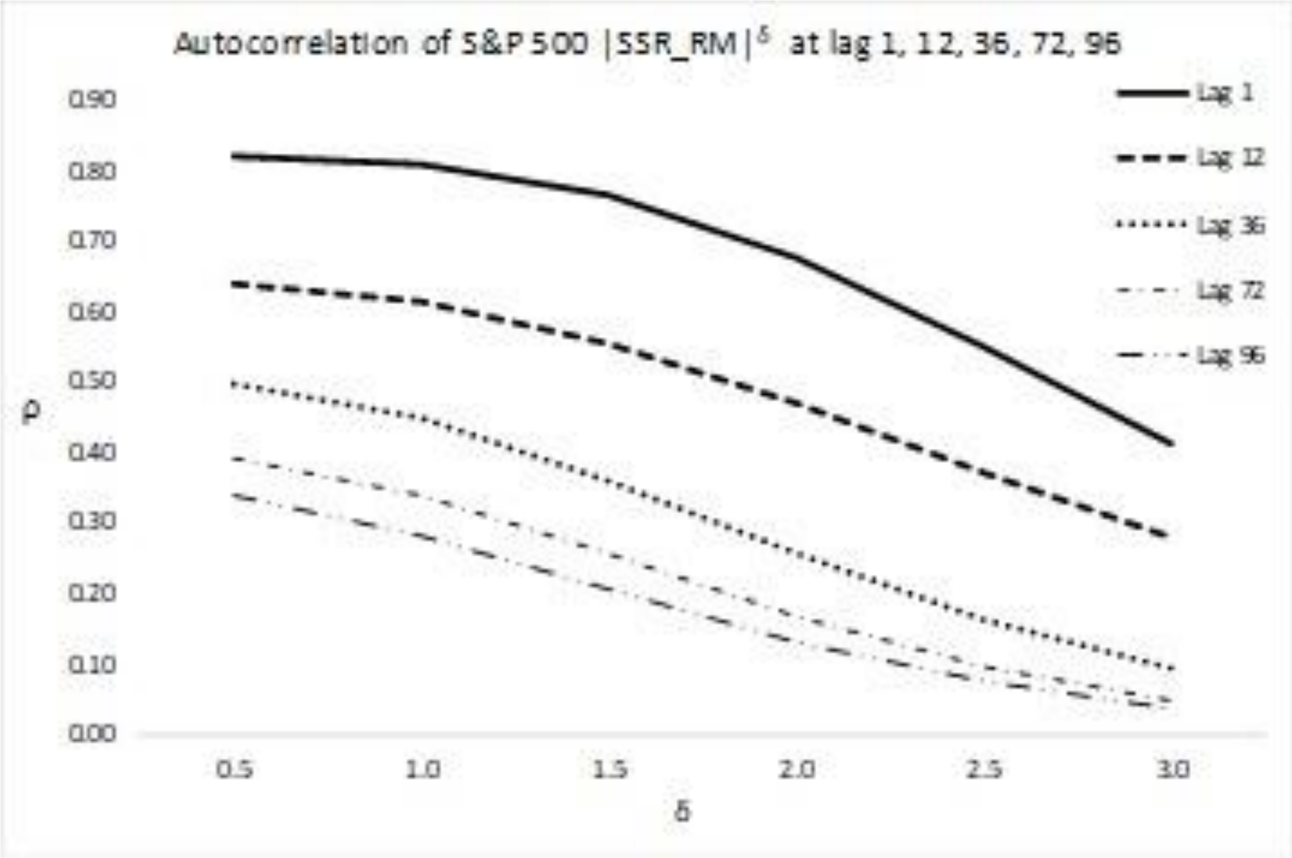

Figure 4. Autocorrelation of S&P 500 $|SSR\_RM_t|^{\delta_R}$ at lags 1, 12, 36, 72, 96

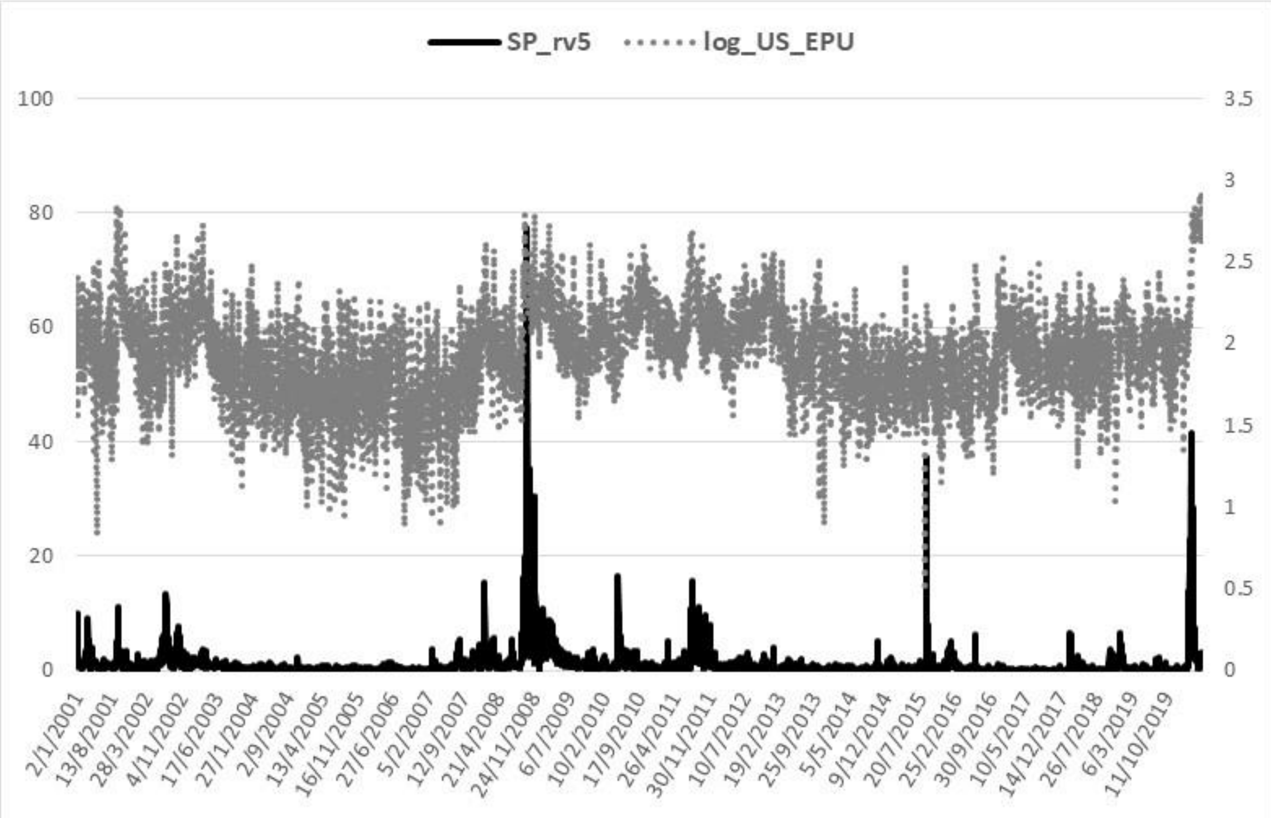

Figure 5. US EPU and S&P 500 Realized Variance

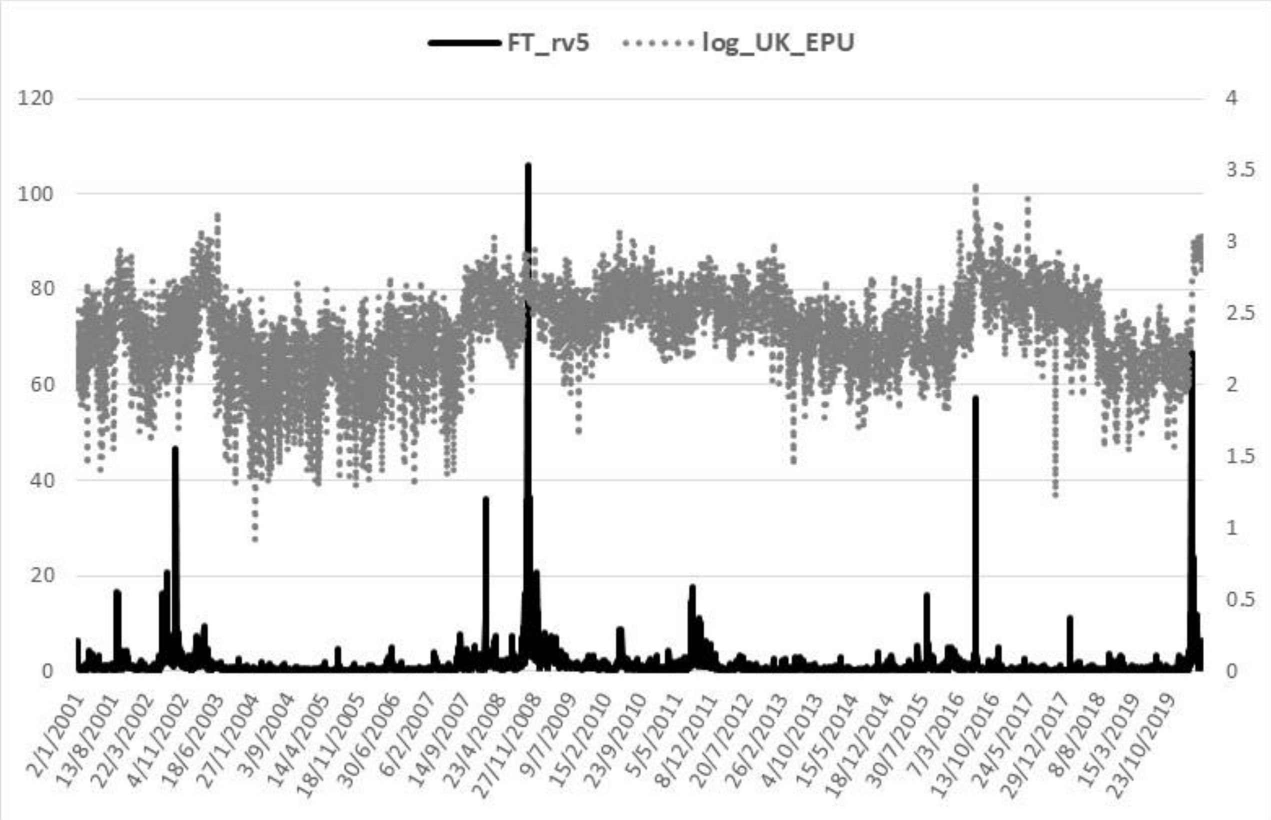

Figure 6. UK EPU and FTSE 100 Realized Variance

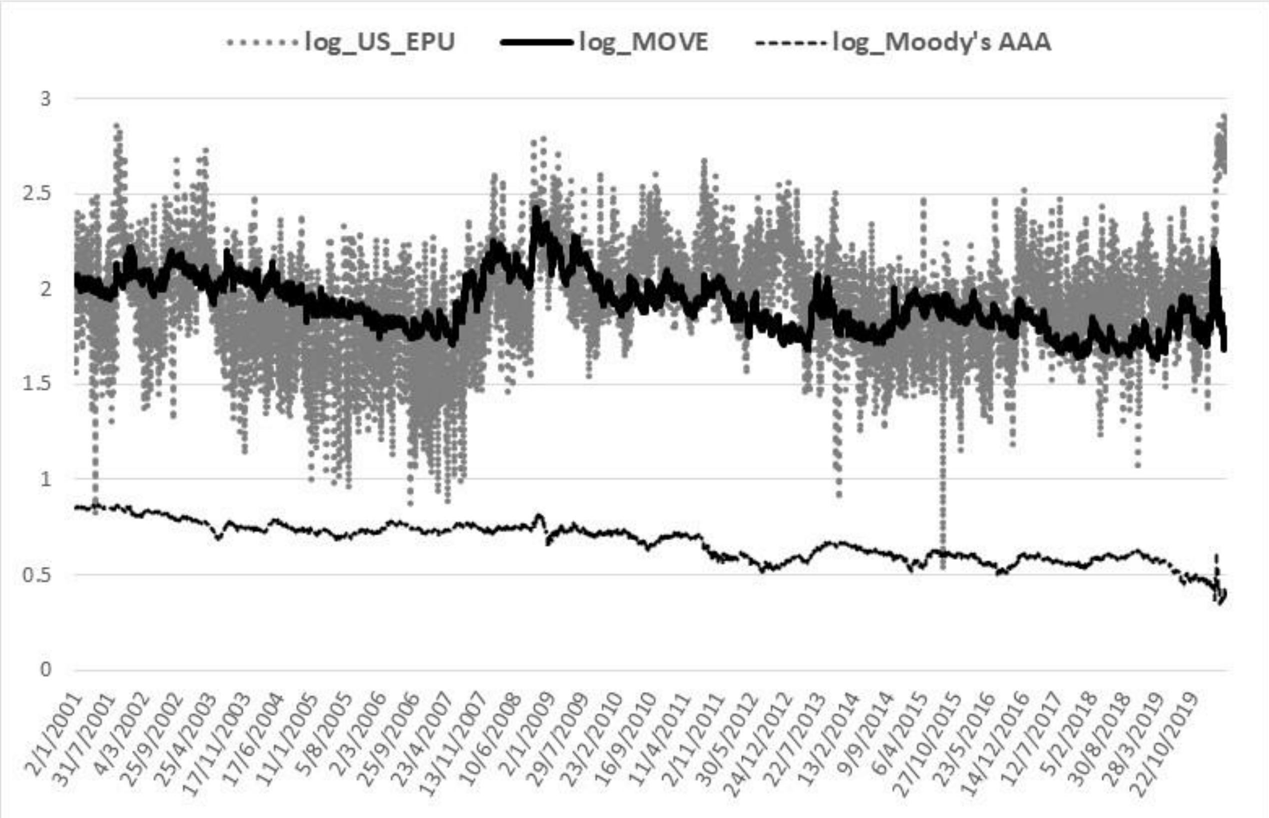

Figure 7. US EPU and the Credit market proxies

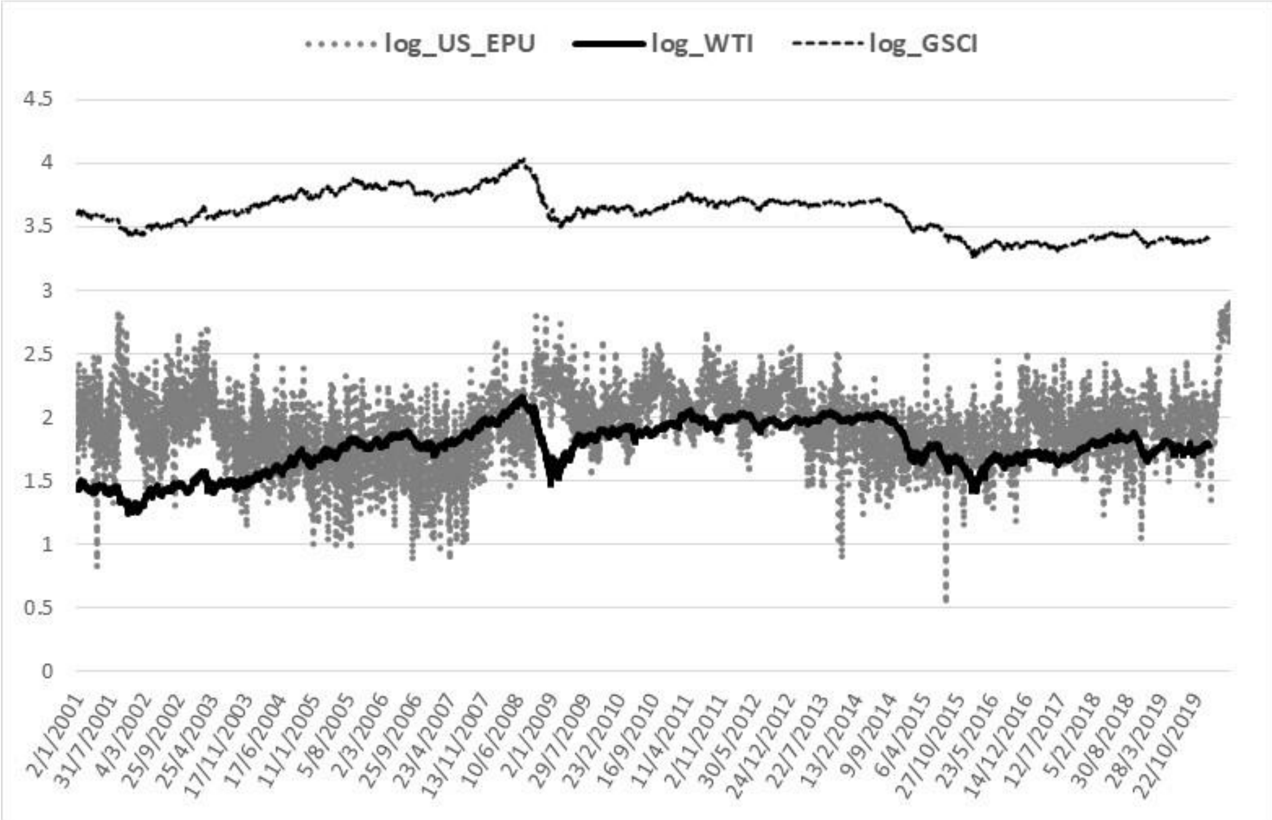

Figure 8. US EPU and the Commodity market proxies

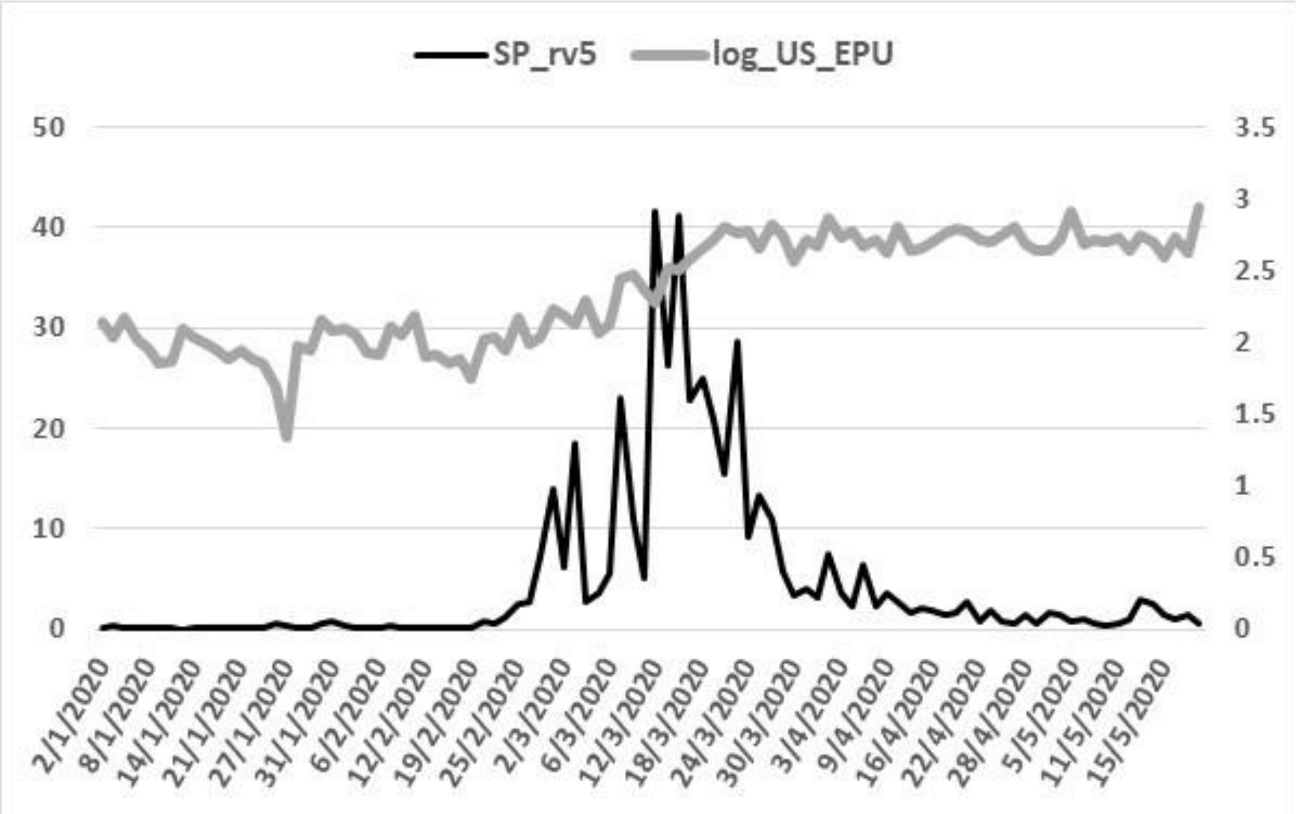

Figure 9. US EPU and S&P 500 Realized Variance (January - May 2020)

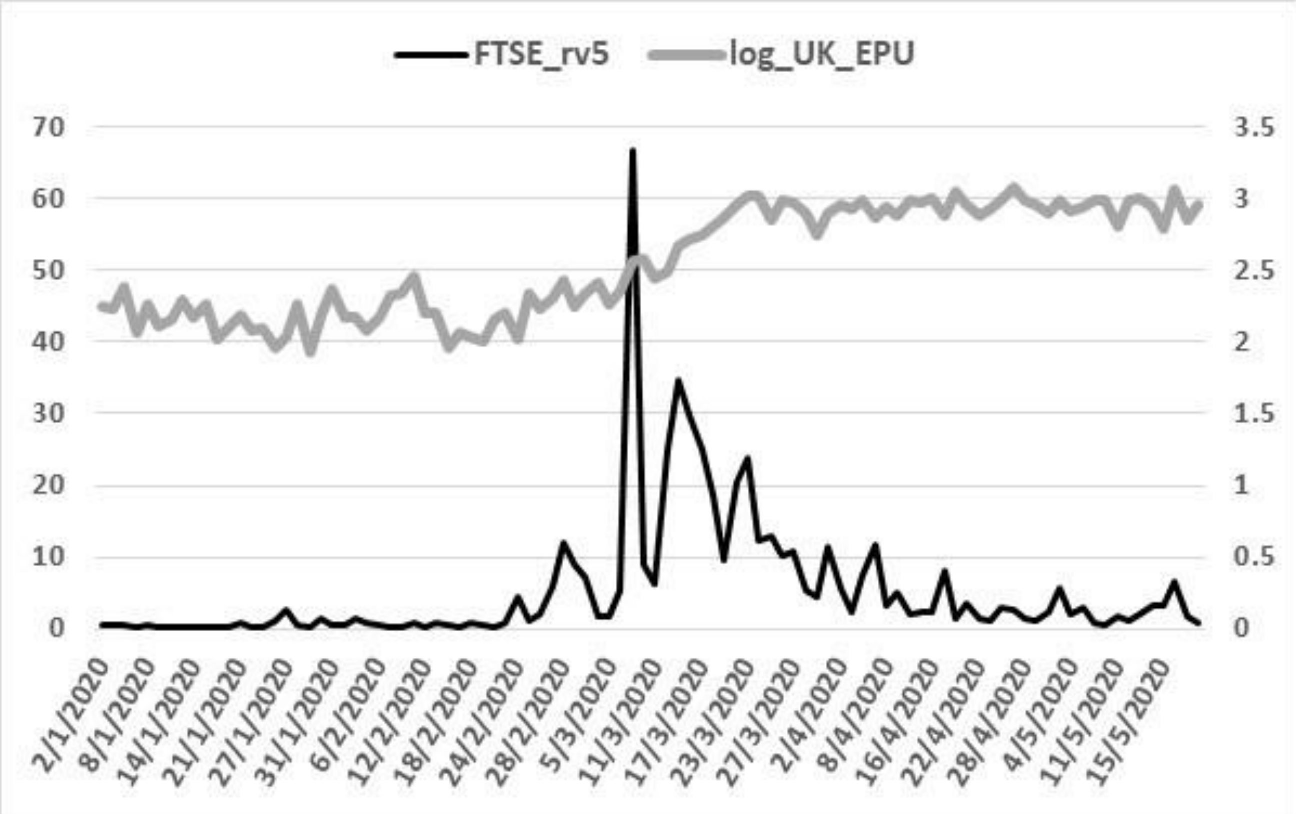

Figure 10. UK EPU and FTSE 100 Realized Variance (January - May 2020)

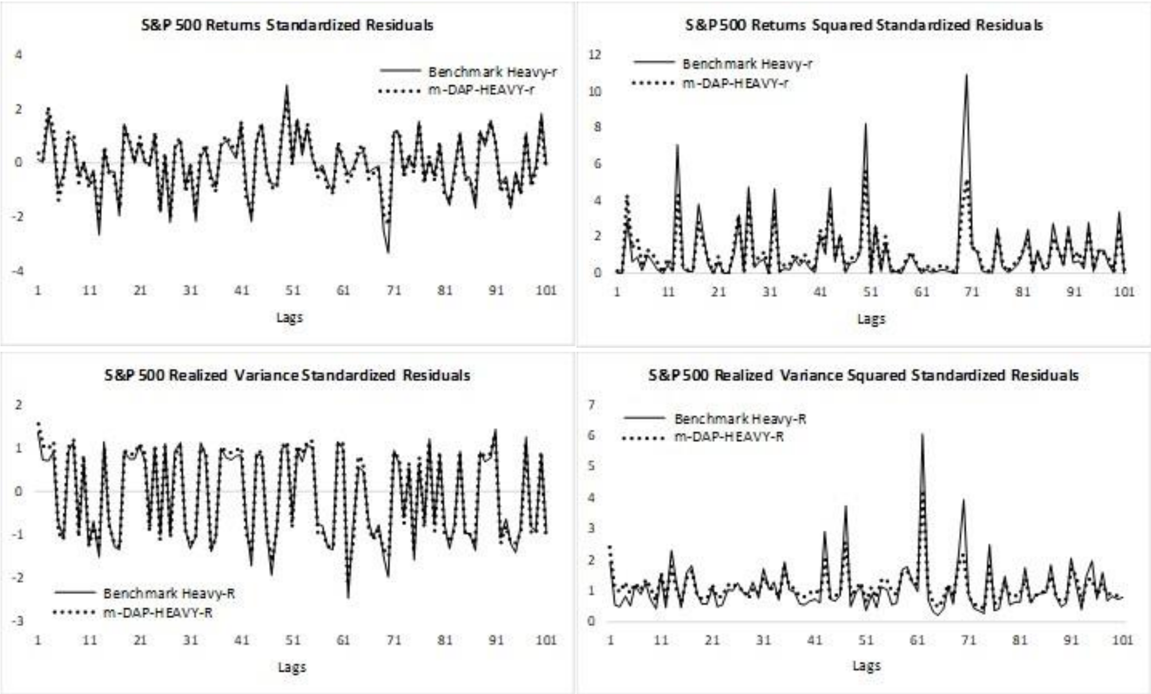

Figure A.1. S&P 500 Standardized Residuals (Benchmark HEAVY and m-DAP-HEAVY models)