Event Study: A High-Frequency Approach

Econometrics

Master's Thesis

Olivia Kvist

Aalborg University
Department of Mathematical Sciences
Thomas Manns Vej 23
DK-9220 Aalborg

This document is typeset with LaTeX. Programming is performed in R.

AALBORG UNIVERSITY
STUDENT REPORT

Department of Mathematical Sciences
Mathematics-Economics
Thomas Manns Vej 23
9220 Aalborg Øst
http://math.aau.dk

Title:

Event Study: A High-Frequency Approach

Theme:

Econometrics

Project Period:

Spring 2024

Student:

Olivia Kvist

Supervisor:

J. Eduardo Vera-Valdés

Page Numbers: 48

Date of Completion:

2nd of August 2024

Abstract:
The thesis is an exposition of my accomplished work during the first two years as a $4+4$ PhD student. It is written to comply with the requirements for the qualification exam, which is a mandatory part of the $4+4$ scheme. The focal points of my research along with two papers, one ongoing and one submitted to a peer-reviewed journal, are introduced. Both papers use the same theory concerning the identification of jumps in high-frequency. The objective is to expand the traditional notion of event studies to a high-frequency setting. We performed a simulation study, to verify that the price jump test captures what is requested. The simulation study shows that the price jump test accurately captures jumps down to a certain price increase. Hereafter, the jump tests were performed on green and brown stocks, surrounding key events during COP28. We find jumps in all analysed green and brown stocks. Lastly, potential research questions for the remaining two years of my PhD are presented.

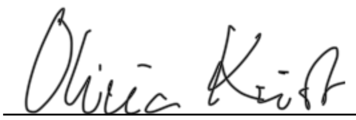
Preface

This thesis is written by Olivia Kvist.

The author would like to thank the supervisor, J. Eduardo Vera-Valdés, for his guidance and motivation throughout the process. Further, the author extends its gratitude to Yossi Bokor Bleile for advice and comments on the content of this thesis.

The code used in Chapters 3 and 4 can be found in the GitHub repository Kvist (2024). The coding has been done in `R`.

Signature



Olivia Kvist
<okvist18@student.aau.dk>

Contents

1 Introduction

There are mainly three aims of this thesis, namely; displaying my contributions during the first two years as a 4+4 PhD student at the Department of Mathematical Sciences, acting as my Master's thesis, and forming the foundation for a meaningful discussion about my plans for the last two years of the PhD study.

The content of this Master's thesis is primarily based on two papers, one in preparation and the other submitted to the Economics Bulletin. The first paper combines event study and high-frequency trade data, with a climate change angle. The working paper version, of the second paper, is available at SSRN (Kvist and Vera-Valdés, 2024). In this paper, we utilise and extend the classical notion of event studies in a high-frequency setting. Thus, we analyse the behaviour of high-frequency trade data of the Tesla stock around certain events.

Additionally, we have a paper on the volatility persistence of stocks related to the climate crisis and more general stocks, called "Effects of the Paris Agreement and the COVID-19 Pandemic on Volatility Persistence of Stocks Associated with the Climate Crisis: A Multiverse Analysis". The analysis of the paper is based on two global events, the Paris Agreement and the COVID-19 pandemic. We find that stocks directly associated with the climate crisis had a decrease in volatility persistence after the Paris Agreement entered into force, whereas the period after COVID-19 showed an increase in volatility persistence of nearly all analysed stocks. The paper is currently in a revise and resubmit stage at Advances in Econometrics; nonetheless, given the different experimental design, it will not be discussed further in this thesis.

The primary topic of my research is climate econometrics. It is well-established that climate change is considered the preeminent challenge of our time because of its severe consequences. Swiss Re released a report in 2021 on the economic effects of climate change (Guo et al., 2021). The report concludes that the global economy will lose approximately 10% of its total value if actions towards climate change are not implemented now.

Additionally, the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, henceforth) has been declared one of the most crucial reports on the possibility of reaching the objectives presented in the Paris Agreement (Bush and Chow, 20/3/2023; McGrath, 9/8/2021). The report demonstrates that the effects of climate change are widespread, with consequences for the planet, human life, and the global economy (IPCC, 2023a).

As such, research in affected areas has increased over the past decade. The research fields explain climate changes and their pace of occurrence. Furthermore, solutions to the problems posed by climate change are also being investigated. Additionally, IPCC wrote in their Sixth Synthesis Report, *"If climate goals are to be achieved, both adaptation and mitigation financing would need to increase many-fold."* (IPCC, 2023b).

A research area that has received extraordinary interest is green finance. The performance of green versus brown financial returns during times of heightened climate change awareness has been examined by various authors (Ardia et al., 2022; Ayaydın Hacıömeroğlu et al., 2022; Pástor et al., 2021; Blasberg et al., 2021). The authors found that the green stocks outperformed the brown during the examined periods. Some researchers also focus on developing a proxy that measures climate change concerns (Ardia et al., 2022; Engle et al., 2020). The significance of such a proxy is that there is empirical evidence that increased perception of climate change often impacts investors' decisions on sustainable investments (Pástor et al., 2021; Engle et al., 2020).

An issue with the current literature is a lack of consensus on the definition and measure of the greenness of a stock. In Bauer et al. (2023) and Blasberg et al. (2021), greenness is measured based on reported CO_2 emissions. Ardia et al. (2022) focuses on S&P500 firms and quantifies their greenness as the ASSET4/Refinitiv carbon-dioxide-equivalent (CO_2-equivalent) greenhouse gas emissions data scaled by the firms' revenue. In Ayaydın Hacıömeroğlu et al. (2022), green bonds are chosen based on the Thomson Reuters database. Further, Pástor et al. (2021) defines an "Environmental, Social and Governance factor" as a scaled return on the ESG portfolio. Moreover, Engle et al. (2020) do not define firms as green, instead, they create a proxy, which measures firms' vulnerability to climate risk. Engle et al. (2020) uses the ESG scores of the firms, provided by Morgan Stanley Capital International, to determine which stocks to use in their portfolios.

Governments, financial institutions, and researchers cannot agree on a formal definition for a green stock or asset. However, several initiatives for green bonds exist, also called climate bonds. Green bonds are where the raised money is earmarked for environmentally friendly projects, e.g., renewable energy (Henry and North, 2023). For example, the International Capital Market Association launched the Green Bond

Principles in 2014 (Green Bond Principle, ICMA Group, 2022), and the EU defines the European Green Bond Standard (The European Council, 2023). Nevertheless, initiatives towards defining green assets, besides bonds, are limited.

In the ongoing paper, we have circumvented the lack of a definition of greenness, by focusing on the energy sector, where the notion of green and brown is more accepted. Thus, our work in that paper is related to the work of Ardia et al. (2022); Ayaydın Hacıömeroğlu et al. (2022); Pástor et al. (2021); Blasberg et al. (2021) since we examine whether news concerning climate change affects the performance of financial assets related to the climate crisis. Due to the news' rapid succession, we use high-frequency trade data to disentangle the events' effects.

The thesis continues as follows: in Chapter 2, we introduce the preliminaries of the used theory. Then we perform a simulation study of high-frequency data with jumps, see Chapter 3. The simulation study should ensure that the used price jump test captures the occurrence of abnormal jumps. We create three simulations; one without jumps, one with randomly occurring jumps, and one with manually inserted jumps. The reasoning for those three types of simulations is to highlight the usage of the price jump test proposed by Lee and Mykland (2008), along with its drawbacks. Afterwards, in Chapter 4, we analyse high-frequency trade data covering the 28th United Nations Climate Change Conference, commonly known as COP28. The stocks under examination are all European-based and within the energy sector. We conclude with a brief description of the plans for the remainder of the PhD study, Chapter 5.

Preliminaries 2

This chapter encompasses the theory I have used thus far in my research. Sections 2.1, 2.2, 2.3, and 2.4 briefly describe high-frequency financial data and the theory behind two types of jump tests. The chapter does not contain proofs which are already well-established by their authors.

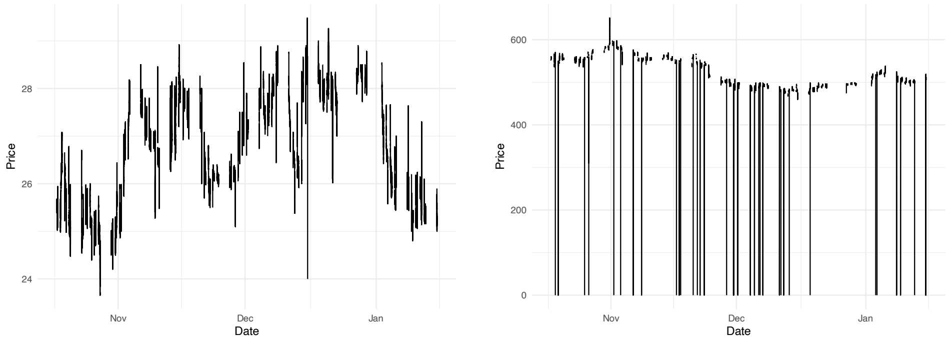
2.1 High-Frequency Data

During the last decade, researchers have paid special attention to the analysis of financial markets using high-frequency trading data. The heightened interest stems from the increased availability, quality, and collection of intraday trade data (Andersen, 2000). High-frequency data is defined as a data point observed every time a trade is made for the financial asset (Hautsch, 2011).

The observation frequency poses several challenges regarding classical statistical and econometric methods and models. One notable problem with high-frequency data is the irregular spacing over time, i.e., due to the data points being recorded at each trade there will not be the same amount of observations per trading day. A financial asset could be traded more than $100,000$ times during a particular day, and then another day it might only be traded $10,000$ times. Therefore, a significant part of working with high-frequency data is the handling and cleaning of it.

2.1.1 Data Handling

We visualise raw high-frequency trade data for two stocks in Figure 2.1. The stocks are Coporación Acciona Energías Revoables, S.A. (ANE.MC, henceforth) and BlueNord ASA (BNOR.OL). ANE.MC is a Spanish utility company working with renewable energy projects whereas BNOR.OL is a Norwegian gas and oil company. The raw data contains observations whenever a trade is made. Hence, the frequency of the prices can be down to a millisecond. Note, that the currency of ANE.MC is EUR, while for BNOR.OL it is NOK.



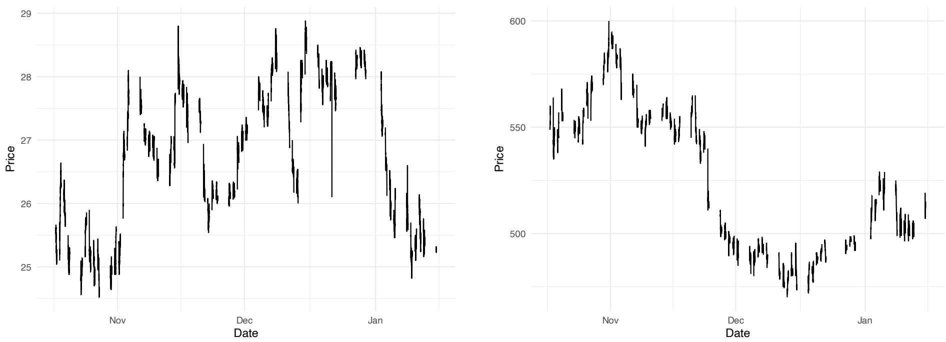
(a) ANE.MC **(b)** BNOR.OL

Figure 2.1: Raw prices of two different stocks. The stock price on the left stems from the Spanish utility company engaged in renewable energy projects both in Spain and internationally. ANE.MC is the stock symbol for Corporación Acciona Energías Renovables, S.A.. The stock price on the right is from the Norwegian gas and oil company. BNOR.OL is the symbol for BlueNord ASA.

As can be seen from especially Figure 2.1b, there appear to be a lot of erroneous observations. The outliers seem to occur at either the end of the trading day or the beginning, and they need to be considered before we make our econometric tests. When analysing the raw data of BlueNord ASA, we see a tendency of zero prices before the opening and after the closing time of the Oslo Stock Exchange. These observations are excluded from the data since we only analyse what happens to the price during trading hours. Further, when we clean the data we remove zero prices altogether since these occur due to faulty reporting (Hautsch, 2011; Brownlees and Gallo, 2006; Boudt et al., 2022).

The next step of the cleaning process is to aggregate the data to ensure equidistant observations since our methods only apply to this. The presence of microstructure noise in high-frequency financial data is well-known (Hansen and Lunde, 2006; Christensen et al., 2014). Liu et al. (2015) compares various estimates of realised variance in high-frequency data. They find nothing beats the 5-minute realised variance, but a close competitor is the 1-minute frequency. Hence, in line with e.g., Hansen and Lunde (2006); Liu et al. (2015), and to minimise the effect of microstructure noise, we aggregate to 5-minute intervals.

The aggregation alone does not ensure equidistant observations, hence we also utilise imputation methods as introduced by Gençay et al. (2001). We impute the missing data by previous-tick interpolation or linear interpolation, when the interval is less than 30 minutes or above, respectively. Figure 2.2 shows the cleaned and aggregated prices of ANE.MC and BNOR.OL. Notice that the faulty reported zero prices, seen in Figure 2.1, are no longer present in Figure 2.2.



(a) ANE.MC **(b)** BNOR.OL

Figure 2.2: Cleaned and aggregated prices of two different stocks. The stock price on the left stems from the Spanish utility company engaged in renewable energy projects in Spain and internationally. ANE.MC is the symbol for Corporación Acciona Energías Renovables, S.A.. The stock price on the right is from the Norwegian gas and oil company. BNOR.OL is the symbol for BlueNord ASA.

2.2 Estimates of Realised Volatility

Volatility is commonly used to describe the amount of risk related to an asset and thereby a possible investment. Therefore, it is important to have a correct estimate to make informed decisions. Realised volatility is a non-parametric subsequent estimate of the variation in the returns.

There are several realised volatility estimates, but the most commonly used is the realised variance (RV, henceforth). Realised variances have been used in financial econometrics for a long time and can be dated back to e.g., Poterba and Summers (1986). The RV is defined as,

$$RV = \sum_{i=1}^{n} r_{t_i}^2, \tag{2.1}$$

where n denotes the number of intraday observations and r_{t_i} is the log return at time t_i. Considering that the RV is the sum of squared log returns, it is not jump-robust, while if a log return contains a jump then its magnitude would be squared. Thus, we need jump-robust estimates, since we are interested in testing for jumps.

2.2.1 Jump-Robust Estimates

A well-established characteristic of financial data is the presence of jumps, found by discontinuities in the price process. These jumps are often misspecified due to the spontaneity of them (Lee and Mykland, 2008; Christensen et al., 2014). The simulation study, in Chapter 4, and the application surrounding COP28 events, Chapter 4, relies on contrasting jump-robust volatility estimates compared to non-robust adaptations.

The most used jump-robust estimate is, as described by Barndorff-Nielsen and Shephard (2004), the realised bipower variation (RBPV). The RBPV is constructed as a normalised sum of products consisting of neighbouring absolute returns,

$$\mathrm{RBPV} = \frac{\pi}{2}\sum_{i=1}^{n-1}|r_{t_i}||r_{t_{i+1}}|, \tag{2.2}$$

n denotes the number of intraday observations, and r_{t_i} is the log return at time t_i. We compare the RBPV to two additional jump-robust estimates suggested by Andersen et al. (2012). They define the median realised variance (MedRV) and minimum realised variance (MinRV) as,

$$\mathrm{MedRV} = \frac{\pi}{6-4\sqrt{3}+\pi}\left(\frac{n}{n-2}\right)\sum_{i=2}^{n-1}\mathrm{med}\left(|r_{t_{i-1}}|,|r_{t_i}|,|r_{t_{i+1}}|\right)^2, \tag{2.3}$$

$$\mathrm{MinRV} = \frac{\pi}{\pi-2}\left(\frac{n}{n-1}\right)\sum_{i=1}^{n-1}\min\left(|r_{t_i}|,|r_{t_{i+1}}|\right)^2, \tag{2.4}$$

n denotes the number of intraday observations and r_{t_i} is the log return at time t_i. MedRV and MinRV reduce returns tainted with jumps by linking them with nearby returns without jumps. Andersen et al. (2012) showed that the MedRV estimator has superior efficiency properties and improved finite-sample robustness to jumps and small returns, compared to the RBPV; hence, MedRV is our preferred specification. Furthermore, MinRV is less efficient than RBPV and has a marginally higher asymptotic variance (Andersen et al., 2012). We include the three estimates for completeness.

2.3 Lee and Mykland Jump Test

In a paper by Lee and Mykland (2008), a new non-parametric test for jumps in asset prices was introduced. Hence, there is no need to make assumptions about the underlying model and structure of the prices.

Lee and Mykland (2008) defines the test statistic as,

$$\mathcal{L}_i = \frac{r_{t_i}}{\widehat{\sigma}_{t_i}}, \tag{2.5}$$

which compares the log return at time t_i, r_{t_i}, to an estimate of the instantaneous volatility, $\widehat{\sigma}_{t_i}$. The instantaneous volatility is estimated using information up to time t_{i-1}. Thus, their statistic identifies if a significant jump occurs in the price process and at what time. The perception of $\mathcal{L}_i$ is, to check whether the log return at time t_i is abnormal, given $\widehat{\sigma}_{t_i}$. We estimate $\widehat{\sigma}_{t_i}$ using the RBPV, MedRV, and MinRV.

Using the jump-robust estimates for the instantaneous volatility ensures that the test statistic is robust to volatility jumps, that might occur before the jump in the price process. Additionally, Lee and Mykland (2008) further adjust the estimation of the RPBV, since they multiply by $1/(K-2)$, where K denotes the window size used to estimate the instantaneous volatility. Lee and Mykland (2008) suggest choosing $K \in [\sqrt{n\_days \cdot n\_obs}, n\_days \cdot n\_obs]$. Thus, all three estimates of instantaneous volatility are adjusted by multiplication with $1/(K-2)$.

The null hypothesis of the Lee and Mykland test (LM, henceforth) is that there is no jump in the interval $(t_{i-1}, t_i]$. Lee and Mykland (2008) show that $\mathcal{L}_i \xrightarrow{D} \mathcal{N}(0,1)$ under the null. However, $\mathcal{L}_i$ diverges if a jump occurs. Thus, they use the below threshold to test the hypothesis,

$$\frac{\max_{i \in \bar{A}_n} |\mathcal{L}_i| - C_n}{S_n} \xrightarrow{D} \xi, \quad \mathbb{P}(\xi \leq \beta^*) = \exp(-\exp(-\beta^*)), \tag{2.6}$$

where

$$\begin{aligned} C_n &= \frac{\sqrt{2\log n}}{\sqrt{\frac{2}{\pi}}} - \frac{\log \pi + \log(\log n)}{2\sqrt{\frac{4}{\pi}\log n}}, \\ S_n &= \frac{1}{\sqrt{\frac{4}{\pi}\log n}}, \\ \beta^* &\equiv -\log(-\log(1-\alpha)), \end{aligned}$$

$\bar{A}_n$ is the set of $i \in \{1, \ldots, n\}$ such that no jumps occur in the interval $(t_{i-1}, t_i]$, n denotes the number of observations in a day, and β^* is a Gumbel variable, thus we do not need to correct for multiple testing (Dumitru and Urga, 2012). Moreover, Nunes and Ruas (2024) confirmed that the normalising constants hold. So we reject the null hypothesis whenever,

$$\frac{|\mathcal{L}_i| - C_n}{S_n} > \beta^*.$$

In addition to testing whether a price jump occurs, it is possible to recover the direction of it by observing the sign of $\mathcal{L}_i$. The sign of $\mathcal{L}_i$ allows us to conclude whether the jump caused the price to go up or down.

Since the LM test statistic is robust to jumps in the instantaneous volatility happening before the jump in the price process, we are also interested in testing whether a jump in volatility occurs on certain days. The theory behind the test for jumps in daily volatility is described in Section 2.4.

2.4 Barndorff-Nielsen and Shephard Jump Test

The volatility jump test is based on contrasting jump-robust against non-robust versions of the instantaneous volatility. Barndorff-Nielsen and Shephard (2004) propose to compare the RBPV in Equation (2.2) with the RV in Equation (2.2).

Therefore, we perform the so-called daily linear jump test (BNS test, henceforth) described in Barndorff-Nielsen and Shephard (2006). The test statistic is given as,

$$\widehat{G} = \frac{\text{RBPV} - \text{RV}}{\sqrt{\frac{1}{n}(\theta - 2)\widehat{\text{IQ}}}} \xrightarrow{D} \mathcal{N}(0,1), \quad \theta = \frac{\pi^2}{4} + \pi - 3, \tag{2.7}$$

where θ is the coefficient related to the integrated quarticity (IQ). The convergence in distribution to the standard normal holds under the null hypothesis of no jumps. Andersen et al. (2012) suggests that the IQ can be consistently estimated by the realised tripower quarticity (RTPQ), which is defined as,

$$\text{RTPQ} = \mu_{\frac{4}{3}}^{-3} \left(\frac{n^2}{n-2} \right) \sum_{i=3}^{n} \left(|r_{t_i}|^{\frac{4}{3}} |r_{t_{i-1}}|^{\frac{4}{3}} |r_{t_{i-2}}|^{\frac{4}{3}} \right), \quad \mu_{\frac{4}{3}} = 2^{\frac{2}{3}} \cdot \frac{\Gamma\left(\frac{7}{6}\right)}{\Gamma\left(\frac{1}{2}\right)}. \tag{2.8}$$

Equivalently with MedRV and MinRV, defined in (2.3) and (2.4), Andersen et al. (2012) developed their estimators to include the IQ. Thus, the direct extensions of the MedRV and MinRV that apply to estimating the IQ, are defined as

$$\text{MedRQ} = \frac{3\pi n}{9\pi + 72 - 52\sqrt{3}} \left(\frac{n}{n-2} \right) \sum_{i=2}^{n-1} \text{med} \left(|r_{t_{i-1}}|, |r_{t_i}|, |r_{t_{i+1}}| \right)^4, \tag{2.9}$$

$$\text{MinRQ} = \frac{\pi n}{3\pi - 8} \left(\frac{n}{n-1} \right) \sum_{i=1}^{n-1} \min \left(|r_{t_i}|, |r_{t_{i+1}}| \right)^4. \tag{2.10}$$

We perform the test for daily jumps in volatility using the RBPV, MedRV, and MinRV, together with the corresponding RTPQ, MedRQ, and MinRQ, respectively.

Simulation Study 3

An exercise done in this Master's thesis, which has not been done in the first two papers during the PhD, is a simulation study.

The main goal of this simulation study is to ensure that the code for the LM test captures jumps in the price process as we want it to. We simulate different price processes based on the Merton Jump Diffusion model (MJD model, henceforth) (Merton, 1976). The chapter is structured as, Section 3.1 outlines the model used for simulation, Sections 3.2, 3.3, and 3.4 displays the results from the simulations. Lastly, Section 3.5 describes a sensitivity analysis of the LM jump test.

3.1 Merton Jump Diffusion Model

The MJD model extends the original notion of the Black-Scholes model by adding a jump part, with a compound Poisson process, to the diffusion consisting of a standard Brownian motion. The initial goal of extending the Black-Scholes model was to circumvent the unrealistic underlying assumptions the model made regarding stock prices. Thus, Merton (1976) defines the model as the following stochastic differential equation,

$$\frac{\mathrm{d}S_t}{S_t} = (\alpha - \lambda k)\mathrm{d}t + \sigma \mathrm{d}B_t + \mathrm{d}J_t, \tag{3.1}$$

where α is the instantaneous expected return on the stock, σ is the instantaneous volatility of the return conditioned on no jumps, and B_t is a standard Brownian motion. Lastly, J_t is the jump component, a compound Poisson process. Note, in Equation (3.1), $\lambda k \mathrm{d}t$ is subtracted from α to ensure the jump component remains unpredictable. J_t has the following properties,

$$J_t = \sum_{i=1}^{N_t} (Y_i - 1), \tag{3.2}$$

$$\log(Y_i) \sim i.i.d. \mathcal{N}(m, \delta^2), \tag{3.3}$$

$$k \equiv \mathbb{E}[Y_i - 1] = \exp\left(m + \frac{\delta^2}{2}\right) - 1. \tag{3.4}$$

From Equation (3.3), we have that the (Y_i) are i.i.d., follow a lognormal distribution, and are independent of B_t and N_t. N_t is a Poisson process with intensity λ, meaning that λ denotes the average amount of jumps occurring in the MDJ model (Matsuda, 2004). Further, k in Equation (3.4) signifies the expected percentage change in the price if a jump occurs, i.e., a Poisson event, where m and δ in Equation (3.4) originates from the mean and variance of $\log(Y_i)$, Equation (3.3). Note, that if $\lambda = 0$ then no jumps occur, and the MDJ model in (3.1) reduces to the original Black-Scholes model.

We simulate from the MJD model by the following procedure;

1. Fix α, σ, λ, m, δ, and initial price S_0.
2. Fix number of days T and total number of observations to simulate, num_obs, calculate $\mathrm{d}t = T/num\_obs$.
3. Define vector of prices as $S_t = \begin{pmatrix} S_0 & 0 & \cdots & 0 \end{pmatrix} \in \mathbb{R}^{num\_obs+1}$.
4. Calculate $k = \exp(m + \delta^2/2) - 1$.
5. For $i \in [1 : num\_obs]$:
   i) Simulate $Z \sim \mathcal{N}(0, 1)$.
   ii) Set $\mathrm{d}B_t = \sqrt{dt} \cdot Z$.
   iii) Simulate jump between t and $t + \mathrm{d}t$ by $J_t = \sum \mathrm{Poi}(\lambda \cdot \mathrm{d}t) \cdot \mathcal{N}(m, \delta^2)$. Note, that if $\lambda = 0$ then $J_t = 0$.
   iv) Update the ith price by

$$S_i := S_{i-1} \exp\left(\left(\alpha - \frac{\sigma^2}{2} - \lambda k\right) \mathrm{d}t + \sigma \mathrm{d}B_t + J_t\right).$$

3.2 No Jumps in the Simulation

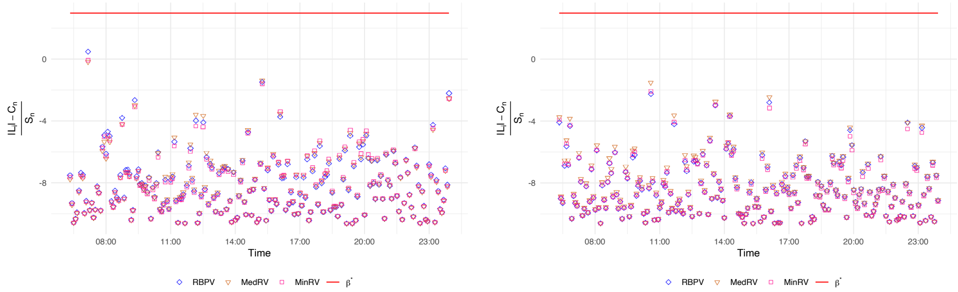
We start by simulating the price process by using the following model,

$$S_t = S_0 \exp\left(\left(\alpha - \frac{\sigma^2}{2}\right) \mathrm{d}t + \sigma \mathrm{d}B_t\right), \tag{3.5}$$

which is just the original Black-Scholes model, meaning there are no jumps in the price process. We fix the model parameters to; $\alpha = 0.05$ and $\sigma = 0.2$. We simulate 20 days with observations every 5 minutes, meaning $num\_obs = 20 \cdot 288 = 5.761$, and therefore $\mathrm{d}t = 20/5.760 = 0.0035$. Figure 3.1 illustrates the simulated price process using the before-mentioned parameter values in the MJD model.

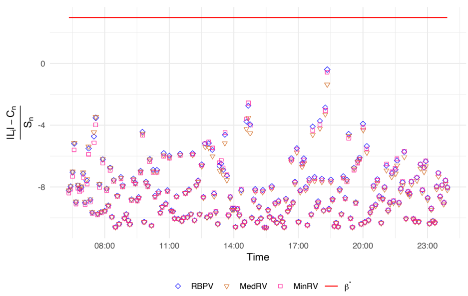
Figure 3.1: Simulation of prices observed at 5-minute frequency over the course of 20 days, resulting in a total of 5.761 data. The prices are generated using the MDJ model in Equation (3.1) with $\lambda = 0$, meaning no jumps occur in the price process.

We perform the LM jump test described in Section 2.3, on the log returns of the above price process. For this exercise, we use $K = \sqrt{20 \cdot 288} = 76$, since we have 20 days worth of data consisting of 288 observations each. Furthermore, we estimate the instantaneous volatility, σ_{t_i}, by the RBPV from (2.2), MedRV (2.3), and MinRV (2.4), respectively. Using all three estimators for σ_{t_i} ensures robustness of the results. Per the simulation model, the result of the LM jump test should be that there are no jumps. We illustrate a subset of the results from the test in Figure 3.1.

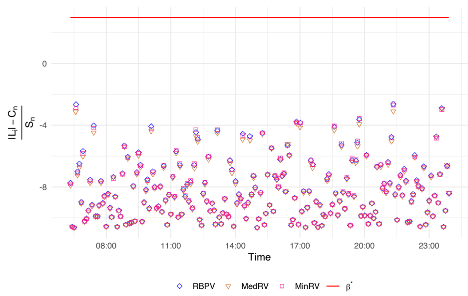


(a) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day three.

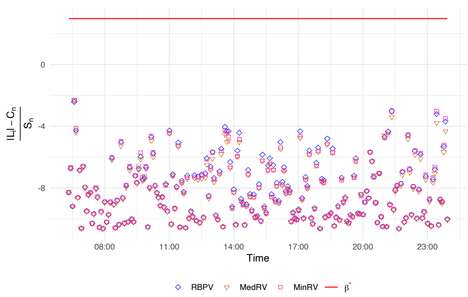
(b) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day four.



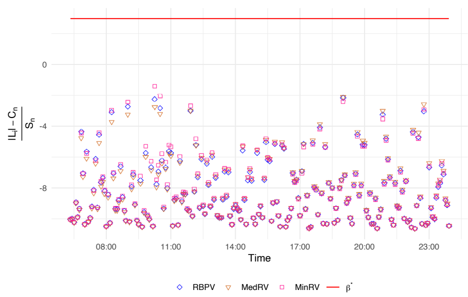
(c) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day five.



(d) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day six.



(e) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day seven.



(f) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day eight.

Figure 3.2: The test statistics from the LM test, $\frac{|\mathcal{L}_i|-C_n}{S_n}$, displayed as either blue (RBPV), brown-orange (MedRV) or pink (MinRV), compared to the critical value β^*, displayed as red horizontal line, based on a 5% significance level.

As Figure 3.2 shows, none of the test statistics exceed the critical value. Therefore, the null hypothesis of no jumps cannot be rejected on any of the tested days. The result of no jumps is what we expected since we simulated from the original Black-Scholes model which does not contain a jump part.

In the next section, we consider simulations from the MJD model with randomly occurring jumps, i.e., $\lambda \neq 0$ in Equation (3.1).

3.3 Jumps in the Simulation

We simulate the price process from the MJD model, i.e., we simulate based on the following,

$$S_t = S_0 \exp\left(\left(\alpha - \frac{\sigma^2}{2} - \lambda k\right)\mathrm{d}t + \sigma \mathrm{d}B_t + \sum_{i=1}^{\mathrm{d}N_t}(Y_i - 1)\right).$$

We fix the coefficients in the model as; $\alpha = 0.05$, $\sigma = 0.2$, $\lambda = 10$, $m = 0$, and $\delta = 0.2$. The value of λ determines the mean number of jumps, thus we simulate a price process with approximately 10 jumps. Further, the value of m and δ entails that $k = 0.02$.

We do as in Section 3.2 and simulate 20 days of 288 observations each. The simulated price process is visualised in Figure 3.3.

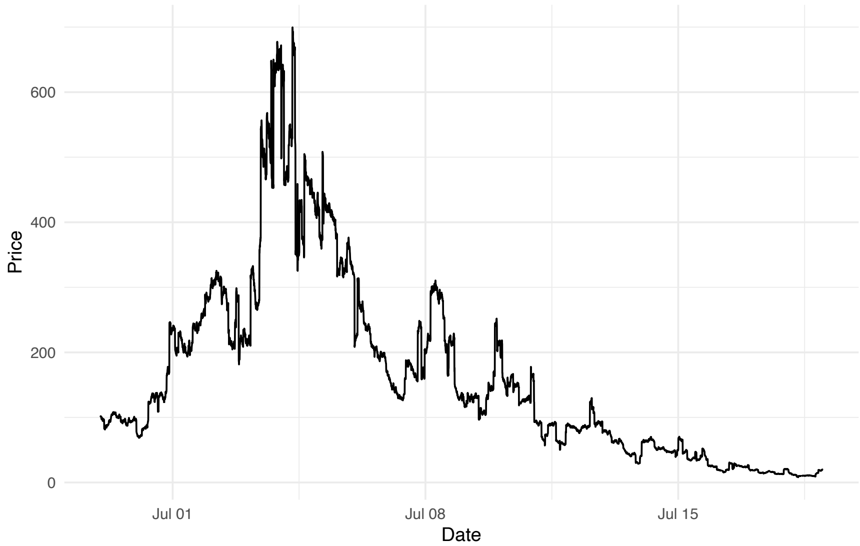


Figure 3.3: Simulation of prices observed at 5-minute frequency over the course of 20 days, resulting in a total of 5.761 data points. The prices are generated using the MDJ model in Equation (3.1) with $\lambda = 10$, meaning an average of 10 jumps per day in the price process.

As seen from Figure 3.3 there appear to be jumps in the price process, especially compared to Figure 3.1, which is expected since $\lambda \neq 0$ in this simulation. The jumps are more easily identified when visualising the log returns,

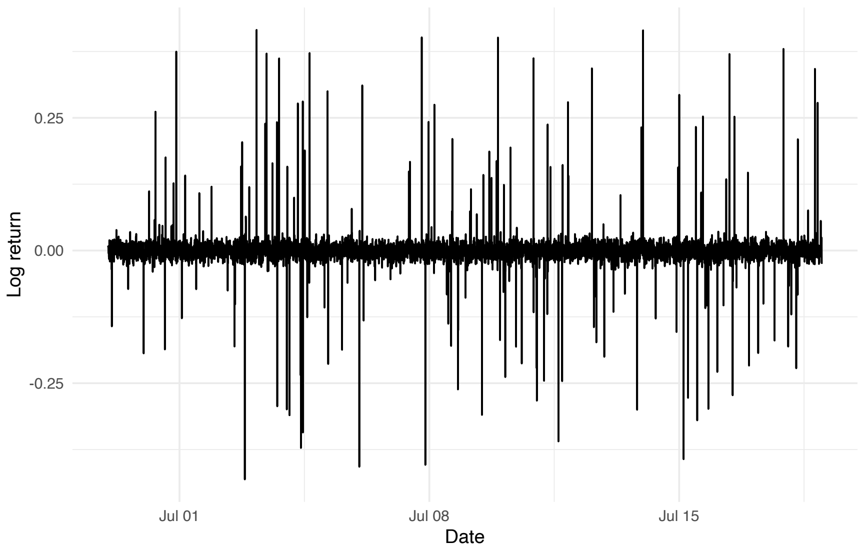
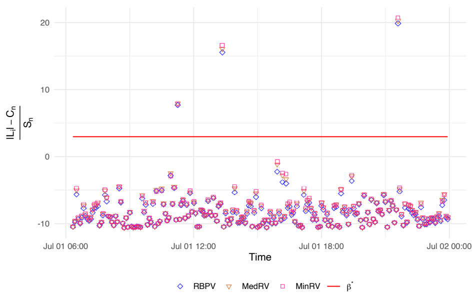
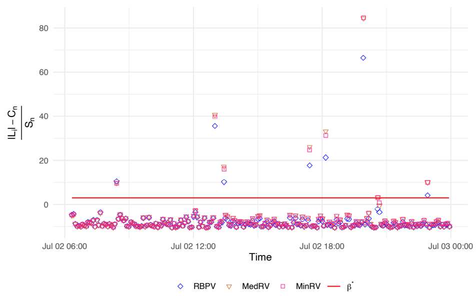


Figure 3.4: The log returns based on the simulated prices, from the MJD model in Equation (3.1) with $\lambda = 10$, seen in Figure 3.3.

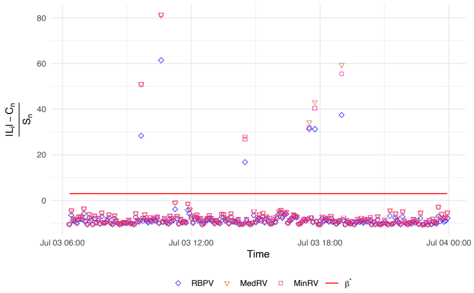
It is evident from Figure 3.4, that the price process, and hence the log returns, contains jumps. The next step is to test whether these jumps are significant using the LM test, defined in Section 2.3. We again choose $K = \sqrt{20 \cdot 288} = 76$ as the window size for estimating the instantaneous volatility. Additionally, we ensure robustness by estimating σ_{t_i} using the RBPV, MedRV, and MinRV. A subset of the results from the LM test is visualised in Figure 3.3. We are testing based on a 5% significance level. The points denote the test statistics, $\frac{|\mathcal{L}_i| - C_n}{S_n}$, and the red horizontal line is the critical value, β^*, for the chosen significance level.



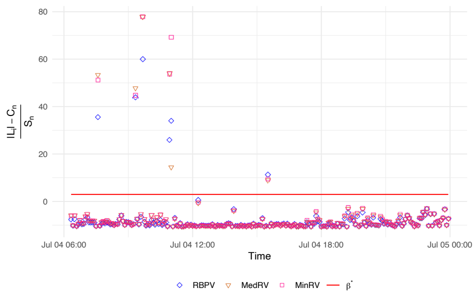
(a) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day three.



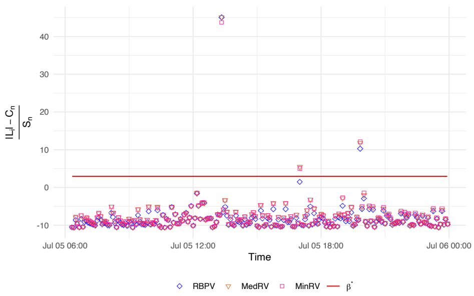
(b) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day four.



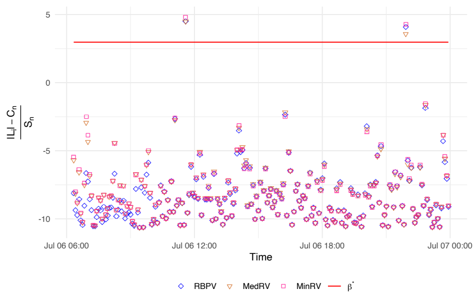
(c) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day five.



(d) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day six.



(e) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day seven.



(f) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day eight.

Figure 3.5: The test statistics from the LM test, $\frac{|\mathcal{L}_i|-C_n}{S_n}$, displayed as either blue (RBPV), brown-orange (MedRV) or pink (MinRV) points, compared to the critical value β^*, displayed as red horizontal line, based on a 5% significance level.

In Figures 3.5a-3.5f, we see significant jumps in the price process on all the visualisations. By recovering the sign of $\mathcal{L}_i$ we can determine if these jumps stem from an increase or decrease in the price. We tabulate the actual value of $\mathcal{L}_i$, whenever the test detects a significant jump for the test in Figure 3.5b, corresponding to day four, in Table 3.1.

	LM Test		
Obs. number	RBPV	MedRV	MinRV
966	-7.0300^{**}	-6.7792^{**}	-6.7152^{**}
1,021	-15.3808^{**}	-17.0534^{**}	-16.755^{**}
1,026	-6.9347^{**}	-9.251^{**}	-8.8926^{**}
1,074	9.4187^{**}	12.2007^{**}	11.7517^{**}
1,083	10.629^{**}	14.5664^{**}	13.9336^{**}
1,104	-25.6544^{**}	-31.6176^{**}	-31.7013^{**}
1,112	2.8434	4.5937^{**}	4.5746^{**}
1,140	4.9078^{**}	6.8626^{**}	6.8892^{**}

Table 3.1: Intraday value of $\mathcal{L}_i$ test statistic, from the LM test described in Section 2.3. The test statistics are calculated based on log returns at 5-minute frequency for the simulated price process in Figure 3.3, corresponding to day four in the simulation. The reported test statistics stem from the points in Figure 3.5b. We estimate the instantaneous volatility by RBPV, MedRV, and MinRV. The 5% significance level of the LM test is reported using **.

Table 3.1 shows that half of the jumps are due to a price increase, while the other half is because of a decrease, with only one discrepancy between the three estimators. The intraday jump at observation $1,112$ is significant if we estimate σ_{t_i} by either MedRV or MinRV, whereas it is deemed insignificant when using the RBPV. The log return for that specific time is 0.0641 based on a change in price from 189.1413 to 201.6686, thus there was a 6% increase from observation $1,111$ to $1,112$. Due to the preferable properties and finite-sample robustness of the MedRV, see Section 2.2.1 and Andersen et al. (2012), we rely on the results from this estimator.

3.4 Manually Inserted Jumps in the Simulation

In this section, we use the simulation in Section 3.2, see Figure 3.1. However, we insert four jumps of our choosing. The jumps are placed in observation 219, 900, $2,385$, and $3,729$ and has magnitude 50%, −40%, 70%, and −30%, respectively. The observations with jumps correspond to the simulated day one, four, nine, and 13, respectively. Figure 3.6 visualises the price process with the aforementioned inserted jumps.

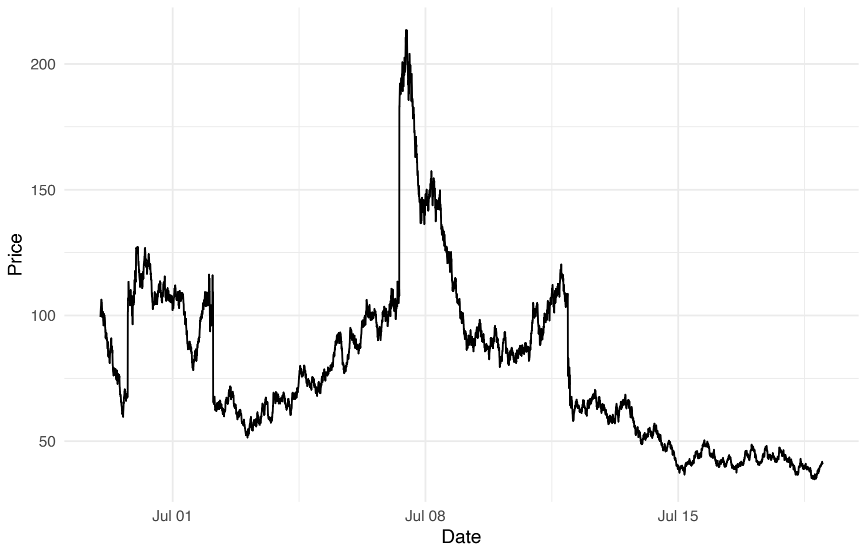
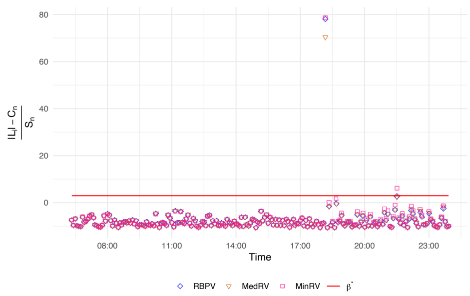
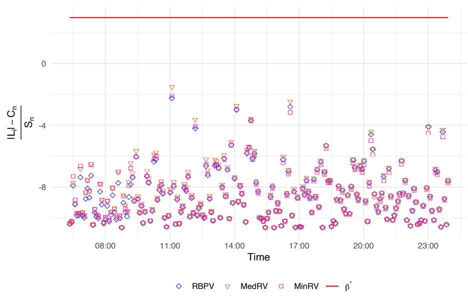


Figure 3.6: Simulation of prices observed at 5-minute frequency over the course of 20 days, resulting in a total of 5.671 data points. The prices are generated using the MJD model in Equation (3.1) with $\lambda = 0$, meaning no jumps occur in the simulation. There are manually inserted jumps in observation 219, 900, 2, 385, and 3, 729.

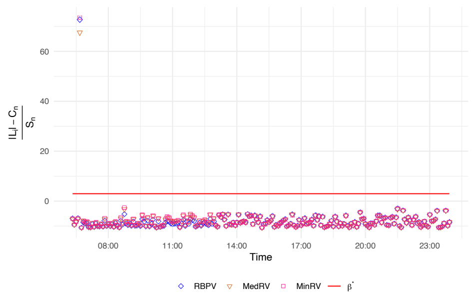
The price jumps are moderate in size. This is because we want to ensure that the LM test using RBPV, MedRV, and MinRV as estimates for the instantaneous volatility captures the jumps. Further, we again use the window size $K = 76$ to estimate σ_{t_i} in Equation (2.5). The jump inserted at observation 900 is strategically placed in the 36th observation of the day, to show that if the jump occurs within the estimation window for σ_{t_i} it will not be reported as a jump. The test statistics, from Equation (2.6), are plotted against the critical value, β^*, in Figure 3.6.



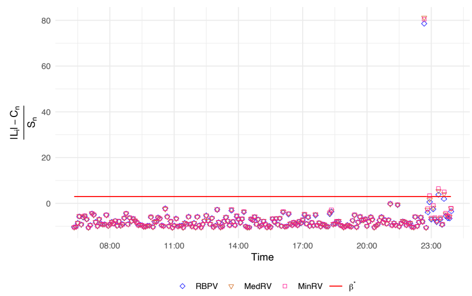
(a) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day one.



(b) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day four.



(c) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for simulated price process day nine.



(d) Test statistic by using the RBPV (blue), MedRV (brown-orange), and MinRV (pink) vs. the critical value (the red line) for the simulated price process day 13.

Figure 3.7: The test statistics from the LM test, $\frac{|\mathcal{L}_i|-C_n}{S_n}$, displayed as either blue (RBPV), brown-orange (MedRV) or pink (MinRV), compared to the critical value β^*, displayed as the red horizontal line, based on a 5% significance level.

As expected, we see no significant jumps when examining Figure 3.7b, this is because it happens within the window used for estimating the instantaneous volatility. The other Figures 3.7a, 3.7c, and 3.7d display between one and four significant jumps per day, captured by various estimates of σ_{t_i}. We tabulate the values of $\mathcal{L}_i$, in Table 3.2, to ensure that the sign is correct based on what type of jump we imposed.

	LM Test		
Obs. number	RBPV	MedRV	MinRV
219	29.5531**	26.9663**	29.7253**
259	4.4427	4.4029	5.5722**
2,385	27.7249**	25.9919**	28.0022**
3,729	−29.6888**	−30.5507**	−30.3220**
3,732	3.7288	4.1145	4.643**
3,737	−4.7969**	−5.3321**	−5.7029**
3,740	4.1906	4.9043**	5.2082**
5,668	−4.183	−4.6992**	−4.4553

Table 3.2: Value of $\mathcal{L}_i$ test statistic, from the LM test described in Section 2.3. The test statistics are calculated based on log returns at 5-minute frequency for the simulated price process in Figure 3.6. We estimate the instantaneous volatility by RBPV, MedRV, and MinRV. The 5% significance level of the LM test is reported using **.

From Table 3.2, we see that the sign of $\mathcal{L}_i$ coincides with the jump being either a price increase or a decrease. However, our test captures more jumps than we imposed, i.e., false positives also known as Type I errors in hypothesis testing. For example, MinRV captures four jumps too many, whereas MedRV captures three extra and RBPV captures one more than imposed.

We have provided further information and understanding of the importance of the size of K in estimating the instantaneous volatility, which was one of the objectives of this simulation study.

3.5 Sensitivity Analysis of LM Test

As shown in Section 3.4, the value of K in the LM test highly impacts the detected number of jumps. However, the jumps we inserted in Section 3.4, displayed in Figure 3.6, were fairly high in magnitude. Thus, we check the sensitivity of the LM test to the size of the jump in this section, while continuing to use $K = 76$. We do the sensitivity analysis by generating one day's worth of data, i.e., 288 observations, with a manually inserted jump in observation 219, and repeat that $1,000$ times. We do this for different jump sizes. The LM test is executed in each repetition using the RBPV, MedRV, and MinRV. We summarise how often the LM test captures the jump for each repetition in Table 3.3.

		Captured Jumps - LM Test		
Jump size	Repetitions	RBPV	MedRV	MinRV
100%	1,000	105.1%	113.6%	122.1%
80%	1,000	105.6%	113.6%	122.1%
50%	1,000	107%	113.6%	122.1%
25%	1,000	112%	113.6%	122.1%
20%	1,000	112.5%	113.6%	122.1%
10%	1,000	114.4%	113.6%	120.6%
5%	1,000	38.3%	32.5%	42.5%

Table 3.3: The percentage of significant jumps captured, based on $1,000$ repetitions of 288 simulated points, where one jump is inserted at observation number 219. The jump size column contains the percentage increases in the price, where we assigned the jump.

As seen, from Table 3.3, the jump tests can accurately identify the inserted jumps down to a 20% increase. Hereafter, the LM jump test overlooks the jump in some repetitions. The biggest failure happens when the jump magnitude is only 5%, where the test fails more than 57.5% of the time. However, when the price increase is only 5% the discussion of whether that is considered an actual jump, or just normal price fluctuations, could be made.

Table 3.3 shows that the jump test captures more jumps than we inserted. On average, the RBPV and MedRV capture fewer extra jumps, when the jump size is between a 100% increase and a 20% increase. The additional jumps correspond to a Type I error, i.e., false positives, which a statistical test can contain. We are working with a significance level of 5%, thus allowing for Type I errors 5% of the time. Further, we see that MedRV and MinRV are consistent in how many additional jumps they capture from 100% increase to 20%, whereas the additional detected jumps from RBPV vary across all jump sizes.

Based on our findings, and the preferred properties described in Andersen et al. (2012), we concentrate our conclusions on the MedRV as the estimator for the instantaneous volatility in the LM test.

We do the same sensitivity test as above, but instead of varying the jump size, we vary the volatility of the MJD model in Equation (3.1). Note, that we still use $\lambda = 0$. We fix a price increase of 80% in observation 219.

		Captured Jumps - LM Test		
Volatility	Repetitions	RBPV	MedRV	MinRV
$\sigma = 0.005$	1,000	100.3%	113.4%	126.2%
$\sigma = 0.01$	1,000	100.6%	117.7%	130.7%
$\sigma = 0.06$	1,000	102.2%	113.4%	122%
$\sigma = 0.6$	1,000	111.2%	112.5%	122.2%
$\sigma = 0.9$	1,000	112.8%	113%	123.7%
$\sigma = 1.5$	1,000	114.4%	112.1%	120.6%
$\sigma = 2.3$	1,000	37.2%	30.6%	42.9%

Table 3.4: The percentage of significant jumps captured, based on 1,000 repetitions of 288 simulated points, where one jump is inserted at observation number 219. The volatility column contains the used size for σ in Equation (3.5).

From Table 3.4, we see that the smaller σ is the more times we capture the right amount of jumps with almost no Type I errors. However, as σ becomes larger we capture more and more jumps, which should not be there, and our test has a harder time capturing the actual jump we have inserted. This result was expected, since the larger σ is the larger fluctuations we see in the price process, meaning a jump should be much bigger if we want our test to capture it as abnormal.

This completes our simulation study, as we have established that our code for the LM test, described in Section 2.3, works as desired. We now proceed to apply the LM test as well as the BNS test on real data.

Contributions 4

This chapter accommodates an overview of my research results during the first two years of my PhD as well as an application of the LM test and BNS test, Sections 2.3 and 2.4, on high-frequency trade data.

I have two papers in collaboration with my supervisor J. Eduardo Vera-Valdés. The first paper is still ongoing and is titled "The Effect of the IPCC's Sixth Synthesis Report on Green and Brown Stocks: A High-Frequency Analysis". The second is submitted to the peer-reviewed journal, Economics Bulletin, titled "The Effect of CEO Public Behaviour on the Company's Valuation: The Case of Tesla and Elon Musk", available at SSRN (Kvist and Vera-Valdés, 2024). Note, that the version available on (Kvist and Vera-Valdés, 2024) is a working paper version, the one submitted to Economics Bulletin is slightly different.

The chapter is structured as follows, Section 4.1 investigates events related to the COP28 meeting and Section 4.2 contains a summary of the results from the two papers mentioned above.

4.1 Jumps around COP28

In this section, we perform the LM and BNS test on 15 green and 15 brown energy stocks based in Europe. The trade data is downloaded from the Eikon Refinitiv database, through Aalborg University's terminals. The frequency of the data is down to milliseconds, but we aggregate to 5-minute intervals to ensure equidistant observations and to circumvent the troubles posed by microstructure noise (Liu et al., 2015). Further, we clean the data using the methods outlined in Section 2.1.

The section continues as follows; first, we give a short motivation about the expectation of jumps. Then, we define the chosen assets and explain why we are working with these, and the events of interest are discussed. Next, we perform the LM test daily, described in Section 2.3. Lastly, we test for volatility jumps using the BNS test, explained in Section 2.4.

4.1.1 Expectation of Jumps

Event studies on financial assets have been performed for a long time, with one of the possibly first publications made by Dolley (1933). In economics and finance, event studies are typically performed on stock prices centred around corporate events, e.g., earnings calls and stock splits. Thus, event studies allow us to retrieve the effect that unanticipated news has on the value of a specific firm (MacKinlay, 1997; Kothari and Warner, 2007). The increased availability of reliable high-frequency financial data has allowed event studies to be performed at intraday level (Huang et al., 2007; Asgharian et al., 2010). However, most event studies are still concerned with macroeconomic news, not general news. As presented in Chapter 1, researchers have been examining the performance of green versus brown stocks, (Ardia et al., 2022; Ayaydın Hacıömeroğlu et al., 2022; Pástor et al., 2021; Blasberg et al., 2021). In line with the current research, we add to the literature by performing jump tests around unanticipated news associated with the climate crisis. We expect to find jumps due to the unpredictable nature of the news and investors caring, thus reacting to this news.

4.1.2 Chosen Assets

We choose the stocks mentioned in Table 4.1 based on which sector they operate in, and that they are all founded in Europe. We use stocks in the energy sector since most agree on a clear distinction between "green" and "brown" energy Ciucci (2022); Ritchie (2022). Thus, we circumvent the troubles around green stocks mentioned in Chapter 1. Additionally, we use the ESG Risk Ratings made by Morningstar Sustainalytics (2024) to ensure that the green energy companies have a "negligible" or "low" risk rating, and the brown a "medium", "high", or "severe" rating. Morningstar Sustainalytics (2024) is one of the largest providers of ESG ratings and is favoured by investors (Wong and Petroy, 2020). Wallace (21/5/2021) describes, that the Sustainalytics ESG Risk Rating (ESG RR) measures the degree of ESG risk the company faces. The risk rating is an absolute measure, which facilitates comparison between industries and companies.

Table 4.1 contains the stocks' symbols and the company name.

Green Companies		Brown Companies	
Symbol	Name	Symbol	Name
ANE.MC	Corporación Acciona Energías Renovables, S.A.	BNOR.OL	BlueNord ASA
EDP.LS	EDP - Energias de Portugal, S.A.	BP.L	BP P.L.C.
EDPR.LS	EDP Renováveis, S.A.	ENOG.L	Energean P.L.C.
ELE.MC	Endesa, S.A.	GALP.LS	Galp Energia, SGPS, S.A.
ENR1n.DE	Siemens Energy AG	HBR.L	Harbour Energy P.L.C.
ERG.MI	ERG S.p.A.	OMVV.VI	OMV AG
GREG.MC	Grenergy Renovables S.A.	ORRON.ST	Orrön Energy AB
ORSTED.CO	Ørsted A/S	PENR.OL	Panoro Energy ASA
SCATC.OL	Scatec ASA	PGE.WA	PGE Polska Grupa Energetyczna S.A.
S92G.DE	SMA Solar Technology AG	R6C0.DE	Shell P.L.C.
TENr.AT	Terna Energy S.A.	REP.MC	Repsol, S.A.
TRN.MI	Terna Rete Elettrica Nazionale S.p.A.	RWEG.DE	RWE AG
VERB.VI	Verbund AG	TETY.ST	Tethys Oil AB
VLTSA.PA	Voltalia S.A.	TLW.L	Tullow Oil P.L.C
VWSB.DE	Vestas Wind Systems A/S	TOTF.DE	TotalEnergies SE

Table 4.1: Green and brown energy companies and their respective stock symbol.

We use the stock symbols explained in Table 4.1 as a reference for the remainder of this chapter.

In Table 4.2 we report the ESG RR, from (Morningstar Sustainalytics, 2024), of the stocks mentioned in Table 4.1.

Green Companies		Brown Companies	
Symbol	**ESG RR**	**Symbol**	**ESG RR**
ANE.MC	Negligible	BNOR.OL	Severe
EDP.LS	Low	BP.L	High
EDPR.LS	Low	ENOG.L	High
ELE.MC	Low	GALP.LS	High
ENR1n.DE	Low	HBR.L	High
ERG.MI	Low	OMVV.VI	Medium
GREG.MC	Negligible	ORRON.ST	Severe
ORSTED.CO	Low	PENR.OL	Severe
SCATC.OL	Low	PGE.WA	High
S92G.DE	Low	R6C0.DE	High
TENr.AT	Low	REP.MC	Medium
TRN.MI	Negligible	RWEG.DE	Medium
VERB.VI	Low	TETY.ST	Severe
VLTSA.PA	Low	TLW.L	High
VWSB.DE	Low	TOTF.DE	Medium

Table 4.2: Green and brown energy companies and their ESG Risk Rating provided by Morningstar Sustainalytics (2024).

We perform the jump tests around identified news related to the COP28 summit, which was held in Dubai, the United Arab Emirates, from the 30th of November 2023 until the 13th of December 2023. The chosen events are specified in Section 4.1.3.

4.1.3 Events Under Investigation

Several monumental decisions were made during the COP28. A major highlight was that during the first day of the meeting, the parties agreed on funding arrangements for addressing loss and damage, which included a dedicated fund under the UNFCCC (United Nations Climate Change, 2023). The fund got a total of USD 700 million right after the agreement. Further, the parties at the meeting gave unparalleled consideration to the link between climate and biodiversity crisis. Lastly, COP28 concluded with an agreement, that has been called "the beginning of the end of the fossil fuel era" (United Nations Climate Change, 2023). The arrangement forms the basis for an abrupt and reasonable transition, established by profound emissions cuts and heightened finance.

We focus on a subset of the focal points at the conference. The dates, and event descriptions, under analysis are outlined in Table 4.3.

Date	Event	Description
Thursday, 30/11/23	Agreement on loss and damage fund	On the first day of the COP28, the parties agreed on a dedicated fund under the UNFCCC to help with loss and damage due to the climate crisis (Harvey and Lakhani, 30/11/2023).
Tuesday, 05/12/23†	Fossil fuel lobbyists at COP28	It was disclosed that at least 2,456 people associated with the oil and gas industries were allowed access to climate talks at COP28. This is the highest number of lobbyists, from the fossil fuel industry, to attend a COP meeting (Lakhani, 05/12/2023).
Saturday, 09/12/23†	Azerbaijan chosen as host for COP29	It was announced that Azerbaijan would host the COP29 meeting, amid replete discussions (Harvey et al., 09/12/2023).
Wednesday, 13/12/23	Transitioning away from fossil fuels	The COP28 was concluded with an agreement on a text, which fortifies countries to transition away from fossil fuels and enhance renewable energy (Worth, 13/12/2023).

Table 4.3: Key highlights from the 28th United Nations Climate Change Conference held in Dubai, the United Arab Emirates. † indicates that the event occurred after the market was closed.

As seen in Table 4.3, the events are close together, making traditional event studies insufficient. However, utilising high-frequency data allows us to disentangle the effects of each event.

We expand the event windows to include the preceding and following days of the dates in Table 4.3. Further, the third event happened on a Saturday, when the stock exchange markets were closed. Hence, we analyse the Friday before, i.e., the 8th of December, and the Monday after, i.e., the 11th of December.

4.1.4 Analysis of Jumps in Daily Returns

We perform the LM test from Section 2.3 on the green and brown stocks presented in Table 4.1. We check for daily jumps in the price process. Thus, we are only interested to see whether there was a jump in the price between the last observations of two consecutive trading days. Therefore, we estimate the instantaneous volatility, σ_{t_i}, using all observations except the last one, on the day before the event we wish to test for. The window size, used for estimating σ_{t_i}, is $K = 102$ and $K = 88$ for ANE.MC and BNOR.OL, respectively. The varying length of K is due to ANE.MC being traded from 09:00 to 17:30 and BNOR.OL is only traded between 09:00 and 16:20. The log return is calculated based on the last observation of the day in question and the preceding day's final observation.

We show the results from the test on the green stock, ANE.MC, and the brown stock, BNOR.OL, in Table 4.4.

	ANE.MC			**BNOR.OL**		
Date	RBPV	MedRV	MinRV	RBPV	MedRV	MinRV
29/11	12.80**	12.99**	12.21**	−4.56**	−4.56**	−4.19**
30/11	6.29**	5.68**	6.04**	2.33	2.45	2.13
01/12	4.99**	4.91**	4.81**	−5.69**	−5.65**	−5.34**
04/12	19.78**	17.95**	19.96**	−17.90**	−16.52**	−16.29**
05/12	−11.88**	−12.94**	−11.11**	4.37**	5.25**	4.24**
06/12	12.82**	11.58**	13.05**	5.05**	4.90**	4.40**
08/12	1.84	1.92	1.78	−2.30	−2.77	−2.17
11/12	−25.10**	−27.70**	−28.78**	−9.63**	−8.28**	−8.86**
12/12	−17.97**	−19.64**	−18.44**	−11.32**	−11.95**	−10.38**
13/12	−3.65	−3.75	−3.51	7.07**	9.09**	8.14**
14/12	48.52**	49.22**	47.02**	−0.32	−0.33	−0.33

Table 4.4: Daily value of $\mathcal{L}_i$, from the LM test. The test statistics are calculated based on log returns at 5-minute frequency for ANE.MC and BNOR.OL on the days in question. We report the 5% significance level of the LM test using **.

Table 4.4 shows many significant jumps in the price process of both ANE.MC and BNOR.OL. From Table 4.4 it is also evident that ANE.MC contains more jumps than BNOR.OL. Further, the jumps of ANE.MC are more frequently positive compared to those of BNOR.OL. Additionally, we see no discrepancy between the significant jumps using different jump-robust estimates for the instantaneous volatility.

The number of negative price jumps surrounding the days up to our final event, which happened on the 13th of December, could be explained by the adverse reaction to the first draft of the text concluding COP28. Several spoke out with outrage that the text did not require a complete termination of fossil fuels, see e.g., (Harvey et al., 11/12/2023; Harvey and Lakhani, 12/12/2023). Thus, a possible explanation for the significant price decreases, surrounding the final release, could be that investors reacted to news about the disappointment regarding ambitions for phasing out fossil fuels.

The results in Table 4.4 suggest that the green stock experiences more unanticipated price movements than the brown. Moreover, we also see a tendency for positive price movements, meaning the green stock becomes more valuable surrounding our events of interest. On the other hand, the brown stock experiences more negative significant price jumps, suggesting that it becomes less valuable during our analysed events.

In Appendix A.1 we display the results from the LM jump test on the rest of the green and brown stocks. More precisely, we display $\mathcal{L}_i$, from Equation (2.5), whenever it was deemed significant at the 5% significance level.

We conclude, that all the green and brown stocks contain daily price jumps around our events of interest. Further, the green stocks tend to experience a price increase whereas the brown ones show signs of a price decrease. These findings are reassuring because they might convey that investors acknowledge the severity of the climate crisis and what consequences could arise from holding too many brown assets, such as fossil fuels.

4.1.5 Analysis of Jumps in Daily Volatility

We proceed to make the BNS test, described in Section 2.4, for the days of interest, displayed in Table 4.3. We perform the BNS test using all three described jump-robust estimates of volatility, namely the RBPV (2.2), MedRV (2.3), and MinRV (2.4). Further, the accompanied estimates of the integrated quarticity are the RTPQ (2.8), MedRQ (2.9), and MinRQ (2.10), respectively.

	ANE.MC			BNOR.OL		
Date	RBPV	MedRV	MinRV	RBPV	MedRV	MinRV
29/11	0.31	−0.85	−0.14	−0.62	0.18	−0.99
30/11	4.45***	4.00***	2.10**	3.29***	1.71*	0.56
01/12	14.16***	3.18***	6.28***	1.18	0.34	−0.16
04/12	0.27	1.26	−0.31	0.29	2.58***	−0.05
05/12	2.22**	0.95	0.42	−0.66	−0.77	−1.65*
06/12	6.27***	6.84***	6.03***	7.52***	7.86***	3.17***
08/12	6.53***	6.99***	6.07***	3.28***	0.39	0.58
11/12	1.62	3.30***	1.18	4.65***	5.52***	1.56
12/12	2.68***	2.70***	0.67	11.51***	19.38***	11.11***
13/12	0.42	0.87	−0.35	2.38**	2.35**	2.18**
14/12	2.07**	5.80***	2.21**	2.33**	2.59***	1.19

Table 4.5: Daily value of $\widehat{G}$, from the LM test. The test statistics are calculated based on log returns at 5-minute frequency for ANE.MC and BNOR.OL on the days in question. The significance levels for the BNS test are reported as *, **, and ***, for the 10%, 5%, and 1%, respectively.

When examining the results of the BNS test on ANE.MC, it is quite clear that there are not as many jumps in volatility as in the price, see Table 4.4. Additionally, there is a larger discrepancy between the different jump-robust estimates, in both ANE.MC and BNOR.OL. First, when using the RBPV and RTPQ as estimates, we find seven significant jumps for both ANE.MC and BNOR.OL. When using MedRV and MedRQ we again find seven for ANE.MC and BNOR.OL, however the dates for significant jumps differ between those estimates. Lastly, using MinRV and MinRQ only results in five significant jumps for ANE.MC and four for BNOR.OL.

However, due to the findings and discussion made by Andersen et al. (2012), we rely on the results from the MedRV and MedRQ since these estimators have preferred power over the others. If we compare the jumps reported in Table 4.4 with the ones in Table 4.5, we quickly see an inconsistency with what dates contain jumps in either the price process or the volatility. Therefore, we report both tests since we can see that they provide complementary evidence.

The results from the BNS tests on the other 28 stocks are visualised in Appendix A.2. When examining Figures A.3 and A.4 it becomes clear, that all the stocks display significant volatility jumps around our events of interest.

4.1.6 Discussion of Results

We find evidence of statistically significant jumps in the price process and volatility of all analysed stocks, see Table 4.1. The jumps occur around our defined events, Table 4.3, which suggests that the market reacted to the news about COP28. The direction of the price jumps from the LM test, see Table 4.4 and Figures A.1 and A.2, suggests that the market, on average, favoured the green stocks around the news related to COP28. Further, the results from the BNS test, Table 4.5 and Figures A.3 and A.4, indicate that the brown stocks experienced more jumps in volatility compared to the green. Hence, it is possible that the brown ones became more risky around our analysed events.

It is important to check if other compelling news happened on the days in question, to establish a stronger connection between the jumps and our events of interest. After a comprehensive search, we could not find any other conclusive explanation for the jumps, regarding traditional economic news, such as earnings calls. Note, that we cannot infer causality between our events and the jumps.

4.2 Summary of Results from Papers

The experimental design, and its results, in Section 4.1, are similar to our findings in the paper "The Effect of the IPCC's Sixth Synthesis Report on Green and Brown Stocks: A High-Frequency Analysis". We analysed the same 15 green and 15 brown stocks, as described in Table 4.1. We found many significant jumps in price and volatility surrounding the release of the Sixth Synthesis Report from the IPCC, which happened on the 20th of March 2023. Our findings confirm the hypothesis that investors care and react to important news about the climate crisis. For more details on the paper, see the document attached to the thesis.

We take a slightly different approach in our second paper, “The Effect of CEO Public Behaviour on the Company’s Valuation: The Case of Tesla and Elon Musk”. We still use the experimental design in Section 4.1, however, we analyse the value of the Tesla stock concerning controversial behaviour from Elon Musk. Tesla is by many considered a green stock, see e.g., (McWhinney, 30/12/2023; Solanki, 22/12/2023; Kabir, 24/03/2024), so we could argue that the angle of climate econometrics is still valid in the paper. We selected four events to investigate; two considered traditional economic news and two with Elon Musk behaving erratically in the public eye. Our findings support the hypothesis that investors are attentive to CEO public behaviour when evaluating their firms. For more details see (Kvist and Vera-Valdés, 2024).

Future Plans 5

5.1 Research Ideas

During my first two years of the PhD, I have focused on expanding the traditional notion of event studies to a high-frequency setting. The work I have done thus far has inspired other interesting research questions. In this section, a short description of two research questions is given. Further, the plan for the ongoing paper on IPCC's influence on green and brown stocks is outlined.

First, my work with event studies has influenced an idea about constructing a so-called *Climate Awareness Index*. Ardia et al. (2022) formulated their daily Media Climate Change Concerns index. They utilise news articles, published by major U.S. newspapers and news wires, regarding climate change. A drawback of their method is that people can have various newsletter subscriptions without being specifically interested in climate change. Thus, their index captures news awareness but not necessarily the public's awareness.

It would be alluring and beneficial to construct a Climate Change Awareness Index, where the majority of the public is targeted. Hence, my supervisor, J. Eduardo Vera-Valdés, and I discussed using data from Google Trends, with all possible search terms used to describe climate change and the climate crisis. The idea is that, if people use Google for a specific search, then that person must be curious about the particular topic. Thus, we should be able to capture the public's interest and awareness about climate change.

Next, is the topic of climate change making natural disasters happen more frequently and increasing the risk of them occurring in the first place (Vernick, 2024). Proper research into the distribution of natural disasters and their density has yet to be done. In a 2022 arXiv paper, Angelini et al. (2022) propose a new time-varying econometric model, the Time-Varying Poisson Autoregressive with Exogenous covariates (TV-PARX). They state that the TV-PARX is an applicable model to describe and forecast time series of counts. Therefore, the other work we want to do is modelling and predicting the changing density and risks of natural disasters, respectively, by using the TV-PARX.

The ongoing paper examines whether important events about climate change affect the price and volatility of 15 green and 15 brown stocks, in line with what was done in Section 4.1. As earlier mentioned the LM and BNS tests contribute complementary evidence in regards to the behaviour of the stocks. Thus, combining these two tests into a simultaneous one, which rejects the null if neither captures a significant jump, could be beneficial. The first step in creating the simultaneous jump test would be to check whether the test statistics for the LM and BNS tests have some dependency. A way to check for the dependency, and its structure, could be to model them using a non-parametric copula. Further, combining a Gumbel distribution with a standard normal needs to be done, since these are the distributions under the alternative hypothesis of jumps in the process.

5.2 Research Stay Abroad

My research stay is yet to be planned, but there are mainly two places under consideration.

The first one is that I visit Associate Professor Chiara Binelli at the University of Bologna. She is working at the Department of Political and Social Sciences. One of her current research interests is using data science to address policy-relevant questions, e.g., climate change. She visited Aalborg University to speak at our second Earth Day Event, which I co-organised, where we discussed the possibility of me joining her for my research stay. Furthermore, we have discussed the project concerning the climate change awareness index.

The other possibility is, that I visit Associate Professor Felix Pretis at the University of Victoria, British Columbia. He is in the Department of Economics and the deputy co-director of the Oxford University project Climate Econometrics at Nuffield College. I had the pleasure of meeting Felix at the 7th conference in Econometric Models of Climate Change. We also discussed the prospect of collaborating on the Google Trends project.

Bibliography

Andersen, T.G., 2000. Some reflections on analysis of high-frequency data. Journal of Business & Economic Statistics 18, 146–153. doi:10.2307/1392552.

Andersen, T.G., Dobrev, D., Schaumburg, E., 2012. Jump-robust volatility estimation using nearest neighbor truncation. Journal of Econometrics 169, 75–93. URL: https://www.sciencedirect.com/science/article/pii/S0304407612000127, doi:10.1016/j.jeconom.2012.01.011.

Angelini, G., Cavaliere, G., D'Innocenzo, E., Angelis, L.D., 2022. Time-Varying Poisson Autoregression. arXiv URL: https://arxiv.org/abs/2207.11003.

Ardia, D., Bluteau, K., Boudt, K., Inghelbrecht, K., 2022. Climate Change Concerns and the Performance of Green vs. Brown Stocks. Management Science URL: https://pubsonline.informs.org/doi/10.1287/mnsc.2022.4636, doi:10.1287/mnsc.2022.4636.

Asgharian, H., Holmfeldt, M., Larson, M., 2010. An event study of price movements following realized jumps. Quantitative Finance 11, 933–946. URL: https://doi.org/10.1080/14697680903369518.

Ayaydın Hacıömeroğlu, H., Danışoğlu, S., Nuray Güner, Z., 2022. For the love of the environment: An analysis of Green versus Brown bonds during the COVID-19 pandemic. Finance Research Letters 47, Article 102576. URL: https://www.sciencedirect.com/science/article/pii/S1544612321005274, doi:10.1016/j.frl.2021.102576.

Barndorff-Nielsen, O.E., Shephard, N., 2004. Power and bipower variation with stochastic volatility and jumps. Journal of Financial Econometrics 2, 1–37. URL: https://doi.org/10.1093/jjfinec/nbh001, doi:10.1093/jjfinec/nbh001.

Barndorff-Nielsen, O.E., Shephard, N., 2006. Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. Journal of Financial Econometrics 4, 1–30. URL: https://doi.org/10.1093/jjfinec/nbi022, doi:10.1093/jjfinec/nbi022.

Bauer, M., Huber, D., Rudebusch, G.D., Wilms, O., 2023. Where is the Carbon Premium? Global Performance of Green and Brown Stocks. CESifo Working Paper No. 10246. doi:10.2139/ssrn.4344418.

Blasberg, A., Kiesel, R., Taschini, L., 2021. Carbon Default Swap – Disentangling the Exposure to Carbon Risk Through CDS. Available at SSRN: doi:10.2139/ssrn.3856993.

Boudt, K., Kleen, O., Sjørup, E., 2022. Analyzing intraday financial data in r: The highfrequency package. Journal of Statistical Software 104, 1–36. URL: https://www.jstatsoft.org/index.php/jss/article/view/v104i08, doi:10.18637/jss.v104.i08.

Brownlees, C., Gallo, G., 2006. Financial econometric analysis at ultra-high frequency: Data handling concerns. Computational Statistics & Data Analysis 51, 2232–2245. URL: https://www.sciencedirect.com/science/article/pii/S0167947306003458, doi:https://doi.org/10.1016/j.csda.2006.09.030. nonlinear Modelling and Financial Econometrics.

Bush, E., Chow, D., 20/3/2023. Now or never: One of the biggest climate reports ever shows time is running out. NBC News URL: https://www.nbcnews.com/science/environment/climate-change-un-ipcc-rcna75670.

Christensen, K., Oomen, R.C., Podolskij, M., 2014. Fact or friction: Jumps at ultra high frequency. Journal of Financial Economics 115, 576–599. doi:10.1016/j.jfineco.2014.07.007.

Ciucci, M., 2022. Renewable energy. European Parliament: Fact Sheets on the European Union URL: https://www.europarl.europa.eu/factsheets/en/sheet/70/renewable-energy.

Dolley, J.C., 1933. Characteristics and procedure of common-stock split-ups. Harvard Business Review 11, 316–326.

Dumitru, A.M., Urga, G., 2012. Identifying jumps in financial assets: A comparison between nonparametric jump tests. Journal of Business & Economic Statistics 30, 242–255. URL: http://www.jstor.org/stable/23243721.

Engle, R.F., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging Climate Change News. The Review of Financial Studies 33, 1184–1216. doi:10.1093/rfs/hhz072.

Gençay, R., Dacorogna, M., Muller, U.A., Pictet, O., Olsen, R., 2001. An Introduction to High-Frequency Finance. Elsevier Science & Technology, San Diego. chapter 3. pp. 37–38.

Green Bond Principle, ICMA Group, 2022. Green Bond Principles (GBP). Green Bond Principles, ICMA Group URL: https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/green-bond-principles-gbp/.

Guo, J., Kubli, D., Saner, P., Swiss Re Institute, 2021. The economics of climate change: no action not an option. Swiss Re Institute. URL: https://www.swissre.com/dam/jcr:e73ee7c3-7f83-4c17-a2b8-8ef23a8d3312/swiss-re-institute-expertise-publication-economics-of-climate-change.pdf.

Hansen, P.R., Lunde, A., 2006. Realized Variance and Market Microstructure Noise . Journal of Business & Economic Statistics 24, 127–161. doi:10.1198/073500106000000071.

Harvey, F., Greenfield, P., Carrington, D., 09/12/2023. Azerbaijan chosen to host Cop29 after fraught negotiations. The Guardian URL: https://www.theguardian.com/environment/2023/dec/09/azerbaijan-host-cop29-fraught-negotiations.

Harvey, F., Greenfield, P., Lakhani, N., Morton, A., Carrington, D., 11/12/2023. Cop28 draft climate deal criticised as 'grossly insufficient' and 'incoherent'. The Guardian URL: https://www.theguardian.com/environment/2023/dec/11/cop28-draft-agreement-calls-for-fossil-fuel-cuts-but-avoids-phase-out.

Harvey, F., Lakhani, N., 12/12/2023. Last-ditch attempt to forge fresh Cop28 deal after original rejected. The Guardian URL: https://www.theguardian.com/environment/2023/dec/12/rich-countries-failing-show-leadership-break-cop28-impasse-activists-say.

Harvey, F., Lakhani, N., 30/11/2023. Agreement on loss and damage deal reached on first day of Cop28 talks. The Guardian URL: https://www.theguardian.com/environment/2023/nov/30/agreement-on-loss-and-damage-deal-expected-on-first-day-of-cop28-talks.

Hautsch, N., 2011. Econometrics of Financial High-Frequency Data. Springer. doi:10.1007/978-3-642-21925-2.

Henry, P., North, M., 2023. What are green bonds and why is this market growing so fast? World Economic Forum URL: https://www.weforum.org/agenda/2023/11/what-are-green-bonds-climate-change/.

Huang, X., Wright, J., Zhou, H., Wongswan, J., Li, G., 2007. Macroeconomic news announcements, financial market volatility and jumps. Working Paper, Duke University .

IPCC, 2023a. Summary for Policymakers [H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.)]. In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi:10.1017/9781009325844.001.

IPCC, 2023b. Summary For Policymakers. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland. doi:10.59327/IPCC/AR6-9789291691647.001.

Kabir, U., 24/03/2024. 14 Best Climate Change Stocks To Buy According to Hedge Funds. Yahoo! Finance URL: https://finance.yahoo.com/news/14-best-climate-change-stocks-195641707.html.

Kothari, S., Warner, J.B., 2007. Chapter 1 - econometrics of event studies**we thank espen eckbo, jon lewellen, adam kolasinski, and jay ritter for insightful comments, and irfan safdar and alan wancier for research assistance., in: Eckbo, B.E. (Ed.), Handbook of Empirical Corporate Finance. Elsevier, San Diego. Handbooks in Finance, pp. 3–36. URL: https://www.sciencedirect.com/science/article/pii/B9780444532657500159, doi:https://doi.org/10.1016/B978-0-444-53265-7.50015-9.

Kvist, O., 2024. Code for Master's Thesis. URL: https://github.com/okvist04/Master.

Kvist, O., Vera-Valdés, J.E., 2024. The Effect of CEO Public Behaviour on the Company's Valuation: The Case of Tesla and Elon Musk. Not yet published, submitted to Economics Bulletin URL: https://ssrn.com/abstract=4734037.

Lakhani, N., 05/12/2023. Record number of fossil fuel lobbyists get access to Cop28 climate talks. The Guardian URL: https://www.theguardian.com/environment/2023/dec/05/record-number-of-fossil-fuel-lobbyists-get-access-to-cop28-climate-talks.

Lee, S.S., Mykland, P.A., 2008. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. The Review of Financial Studies 21, 2535–2563. URL: https://doi.org/10.1093/rfs/hhm056, doi:10.1093/rfs/hhm056.

Liu, L.Y., Patton, A.J., Sheppard, K., 2015. Does anything beat 5-minute rv? a comparison of realized measures across multiple asset classes. Journal of Econometrics 187, 293–311. URL: https://www.sciencedirect.com/science/article/pii/S0304407615000329, doi:10.1016/j.jeconom.2015.02.008.

MacKinlay, A.C., 1997. Event Studies in Economics and Finance. Journal of Economic Literature 35, 13–39. URL: http://www.jstor.org/stable/2729691.

Matsuda, K., 2004. Introduction to Merton jump diffusion model. Department of Economics, The Graduate Center, The City University of New York URL: https://www.maxmatsuda.com/Papers/Intro/Intro%20to%20MJD%20Matsuda.pdf.

McGrath, M., 9/8/2021. Climate change: IPCC report is 'code red for humanity'. BBC News URL: https://www.bbc.com/news/science-environment-58130705.

McWhinney, J., 30/12/2023. Top Green Investing Opportunities. Investopedia URL: https://www.investopedia.com/articles/stocks/07/green-industries.asp.

Merton, R.C., 1976. Option pricing when underlying stock returns are discontinuous. Journal of Financial Economics 3, 125–144. URL: https://www.sciencedirect.com/science/article/pii/0304405X76900222, doi:https://doi.org/10.1016/0304-405X(76)90022-2.

Morningstar Sustainalytics, 2024. Company ESG Risk Ratings. Morningstar Sustainalytics URL: https://www.sustainalytics.com/esg-ratings.

Nunes, J.P.V., Ruas, J.P., 2024. A note on the gumbel convergence for the lee and mykland jump tests. Finance Research Letters 59, 104814. URL: https://www.sciencedirect.com/science/article/pii/S1544612323011868, doi:https://doi.org/10.1016/j.frl.2023.104814.

Poterba, J.M., Summers, L.H., 1986. The persistence of volatility and stock market fluctuations. The American Economic Review 76, 1142–1151. URL: http://www.jstor.org/stable/1816476.

Pástor, L., Stambaugh, R.F., Taylor, L.A., 2021. Sustainable investing in equilibrium. Journal of Financial Economics 142, 550–571. URL: https://www.sciencedirect.com/science/article/pii/S0304405X20303512, doi:10.1016/j.jfineco.2020.12.011.

Ritchie, H., 2022. What are the safest and cleanest sources of energy? Our World in Data URL: https://ourworldindata.org/safest-sources-of-energy.

Solanki, J., 22/12/2023. Best Climate Change Stocks for 2024. Admiral Markets URL: https://admiralmarkets.com/education/articles/shares/climate-change-stocks.

The European Council, 2023. Sustainable finance: Provisional agreement reached on European green bonds. Council of the EU URL: https://europa.eu/!cKYQGf.

United Nations Climate Change, 2023. Key highlights from COP 28. United Nations Climate Change URL: https://unfccc.int/cop28/5-key-takeaways?gad_source=1&gclid=CjwKCAjw74e1BhBnEiwAbqOAjKhOcJmA5dT7AeqL8-fWZPhk_EwlKrqiipKNWmJ9mbSnOnwfiLhypxoCI84QAvD_BwE#loss-and-damage.

Vernick, D., 2024. Is climate change increasing the risk of disasters? World Wildlife URL: https://www.worldwildlife.org/stories/is-climate-change-increasing-the-risk-of-disasters.

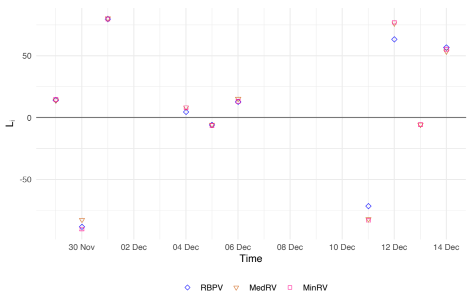
Wallace, K., 21/5/2021. Our New Rating Measures a Stock's ESG Risk. Morningstar URL: https://www.morningstar.com/articles/1039219/our-new-rating-measures-a-stocks-esg-risk.

Wong, C., Petroy, E., 2020. Rate the Raters 2020: Investor Survey and Interview Results. The SustainAbility Institute by ERM URL: https://www.sustainability.com/globalassets/sustainability.com/thinking/pdfs/sustainability-ratetheraters2020-report.pdf.

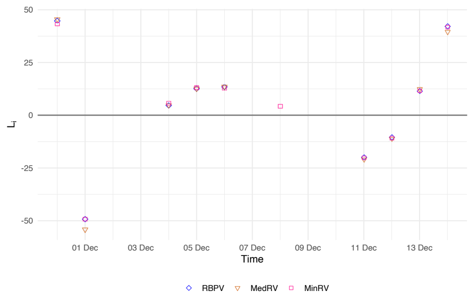
Worth, K., 13/12/2023. COP28 Agreement Signals "Beginning of the End" of the Fossil Fuel Era. United Nations Climate Change URL: https://unfccc.int/news/cop28-agreement-signals-beginning-of-the-end-of-the-fossil-fuel-era.

Appendix A

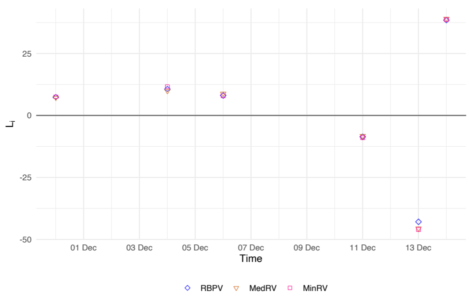
A.1 Daily Price Jumps



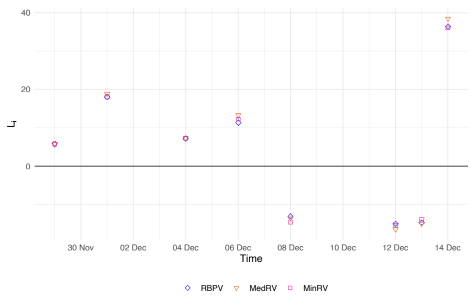
(a) EDP.LS



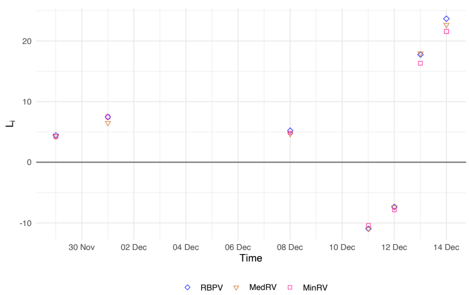
(b) EDPR.LS



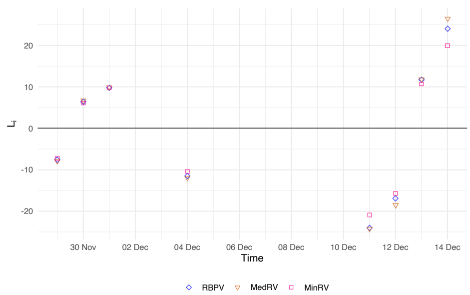
(c) ELE.MC



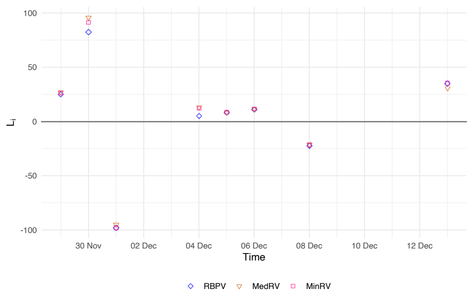
(d) ENR1n.DE.



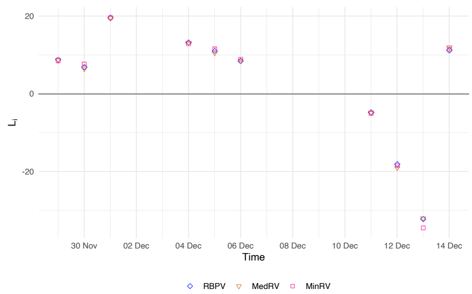
(e) ERG.MI



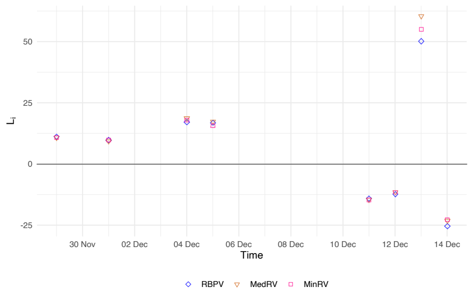
(f) GREG.MC



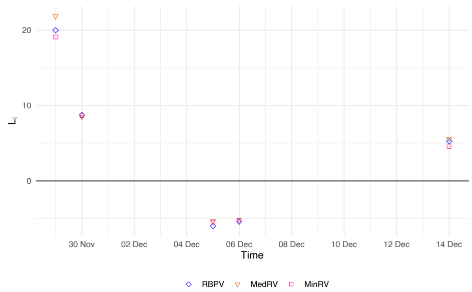
(g) ORSTED.CO



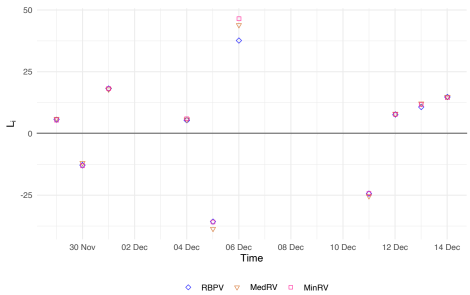
(h) S92G.DE



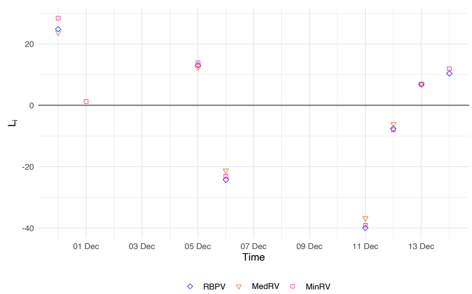
(i) SCATC.OL



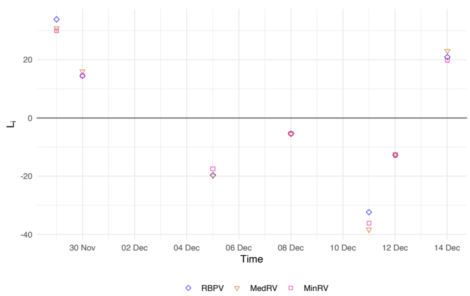
(j) TENr.AT



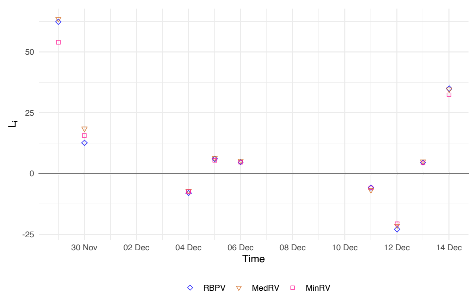
(k) TRN.MI



(l) VERB.VI

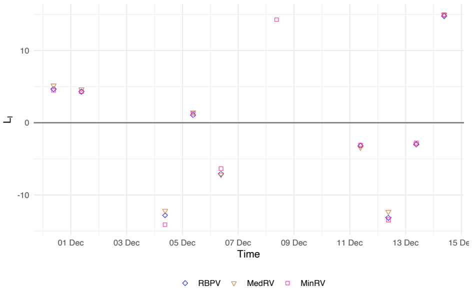


(m) VLTSA.PA

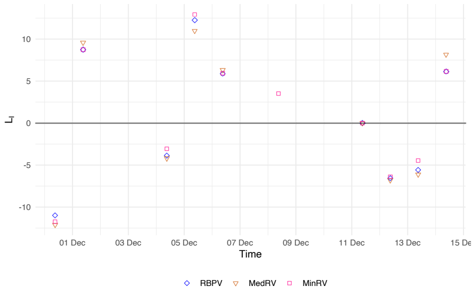


(n) VWSB.DE

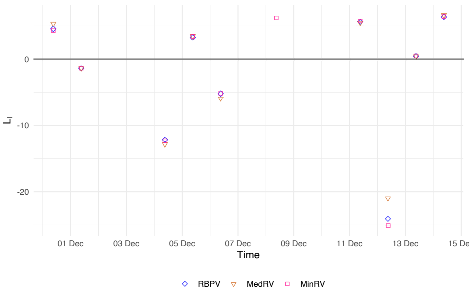
Figure A.1: Daily value of $\mathcal{L}_i$, plotted if significant at a 5% significance level, for the green stocks. The blue points are used when the RBPV is the estimator of σ_{t_i}, the brown-orange points are for MedRV, and the pink points are MinRV. The black horizontal line signifies 0, so points below that suggest a price decrease and above it are price increases.



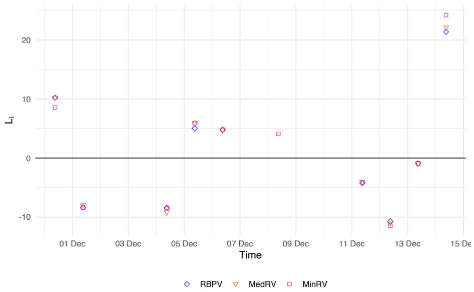
(a) BP.L



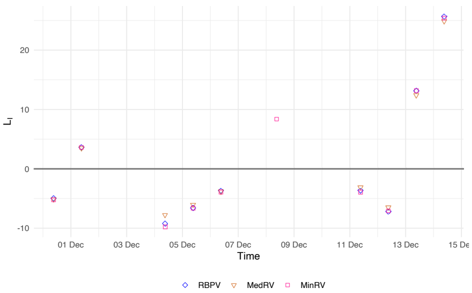
(b) ENOG.L



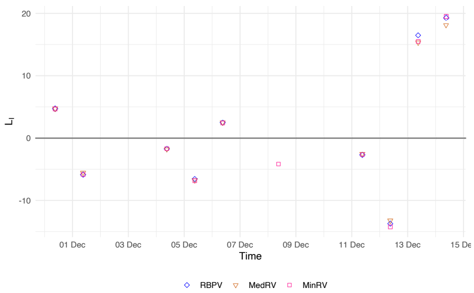
(c) GALP.LS



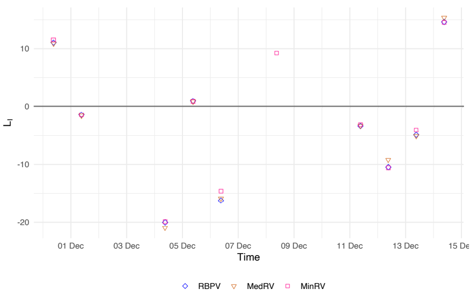
(d) HBR.L



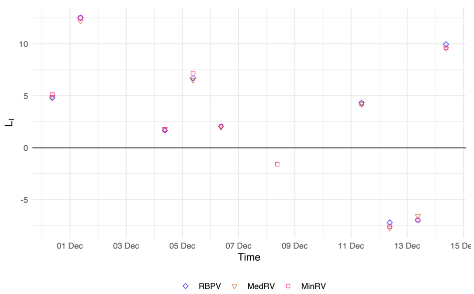
(e) OMVV.VI



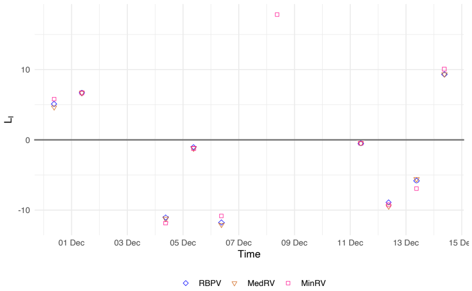
(f) ORRON.ST



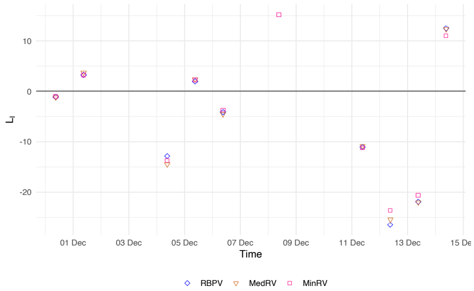
(g) PENR.OL



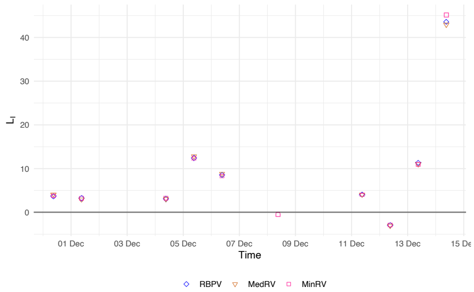
(h) PGE.WA



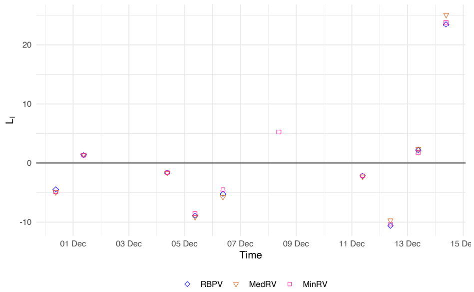
(i) R6C0.DE



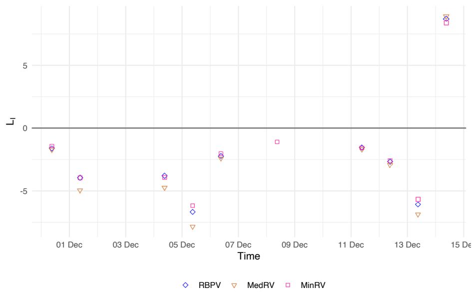
(j) REP.MC



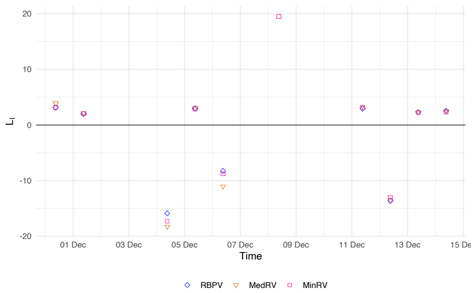
(k) RWEG.DE



(l) TETY.ST



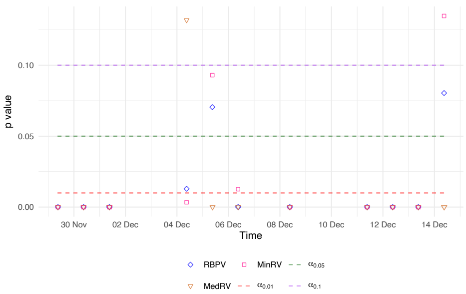
(m) TLW.L



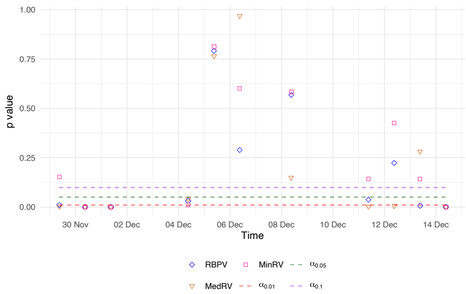
(n) TOTF.DE

Figure A.2: Daily value of $\mathcal{L}_i$, plotted if significant at a 5% significance level, for the brown stocks. The blue points are used when the RBPV is the estimator of σ_{t_i}, the brown-orange points are for MedRV, and the pink points are MinRV. The black horizontal line signifies 0, so points below that suggest a price decrease and above it are price increases.

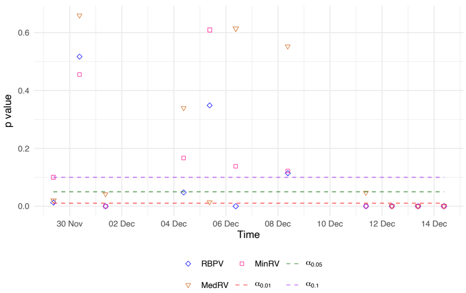
A.2 Daily Jumps in Volatility



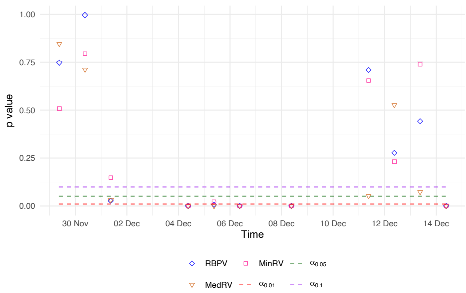
(a) EDP.LS



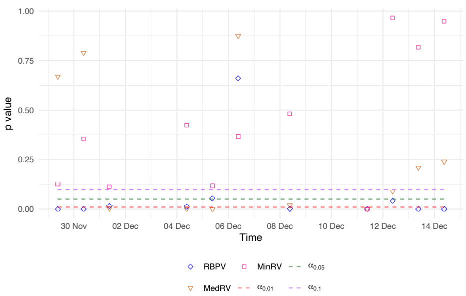
(b) EDPR.LS



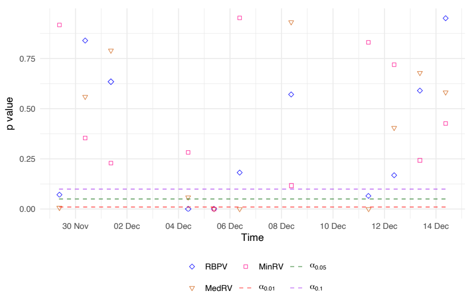
(c) ELE.MC



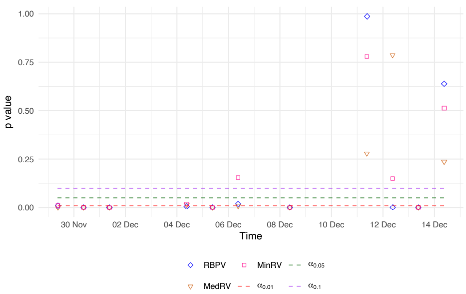
(d) ENR1n.DE.



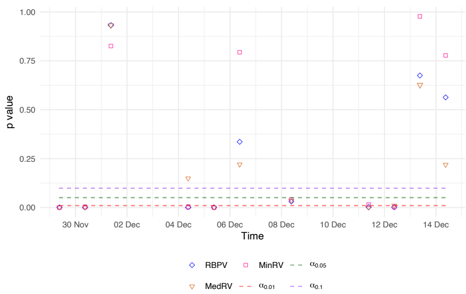
(e) ERG.MI



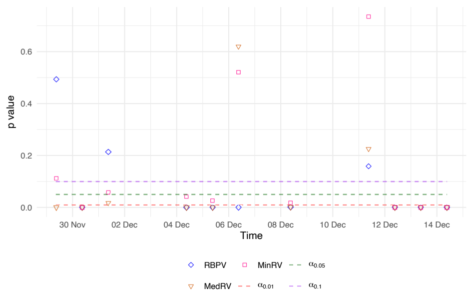
(f) GREG.MC



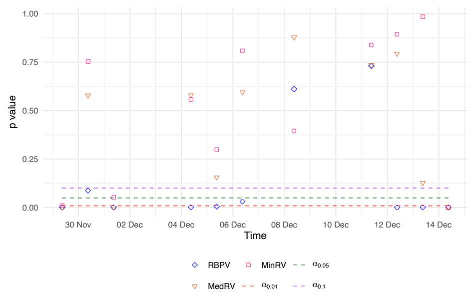
(g) ORSTED.CO



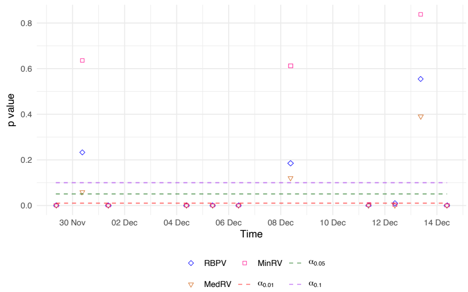
(h) S92G.DE



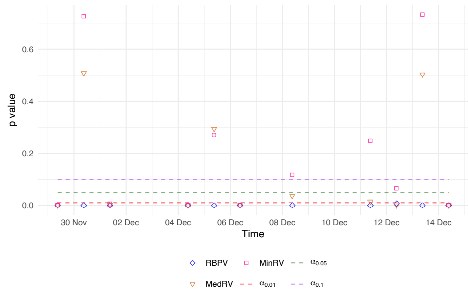
(i) SCATC.OL



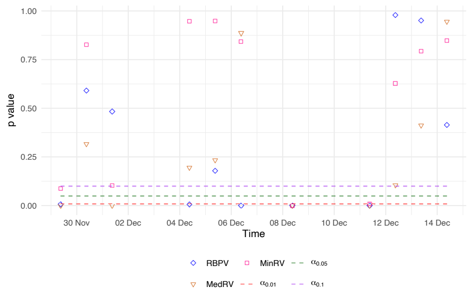
(j) TENr.AT



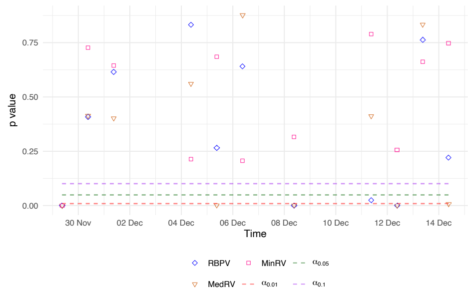
(k) TRN.MI



(l) VERB.VI

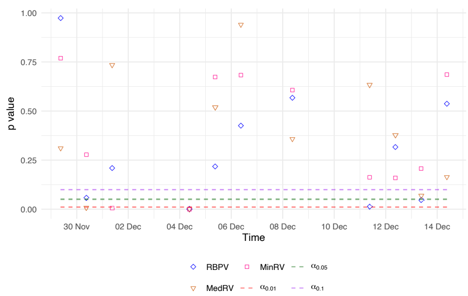


(m) VLTSA.PA

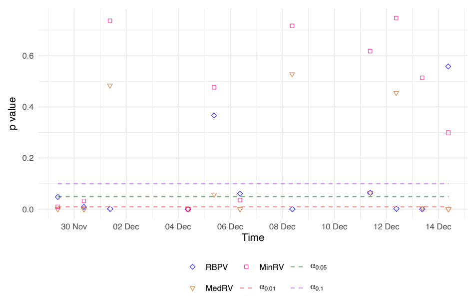


(n) VWSB.DE

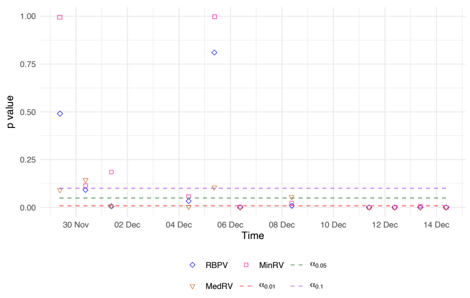
Figure A.3: Daily value of $\widehat{G}$ for the green stocks. The blue points are used when the RBPV is the used jump-robust estimate, the brown-orange points are for MedRV, and the pink points are MinRV. The dashed horizontal lines signify different significance levels; the purple is 10%, the green is 5%, and the red is 1%.



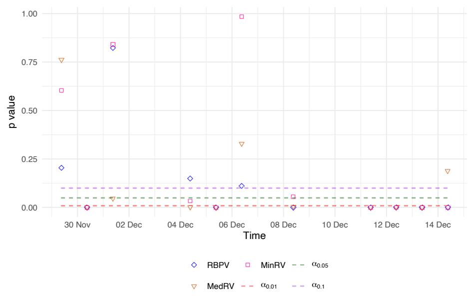
(a) BP.L



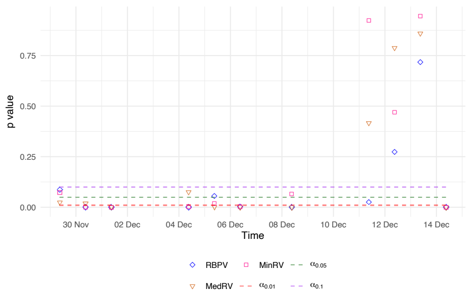
(b) ENOG.L



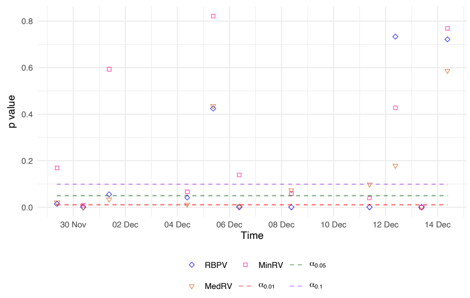
(c) GALP.LS



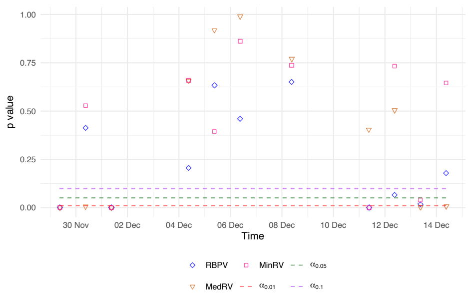
(d) HBR.L



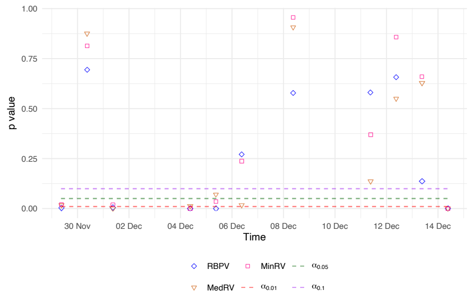
(e) OMVV.VI



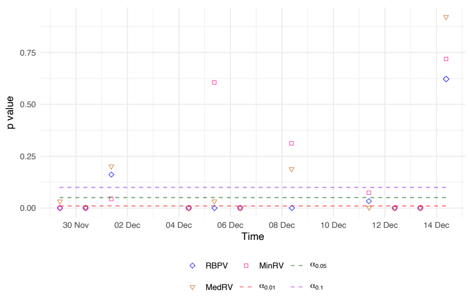
(f) ORRON.ST



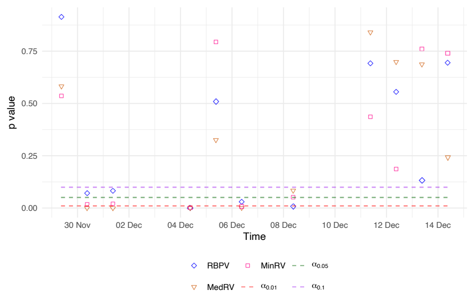
(g) PENR.OL



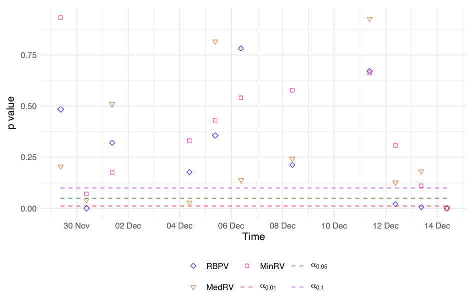
(h) PGE.WA



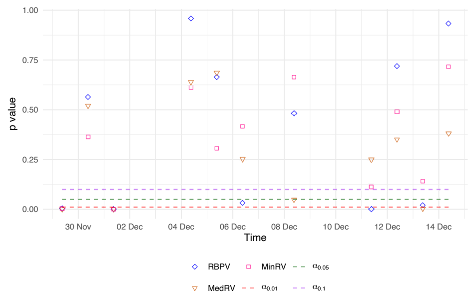
(i) R6C0.DE



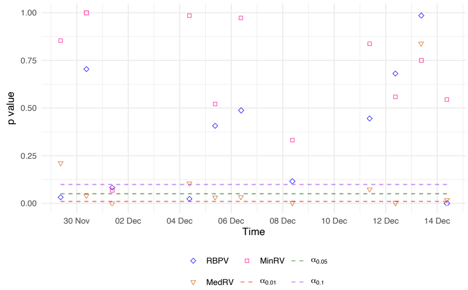
(j) REP.MC



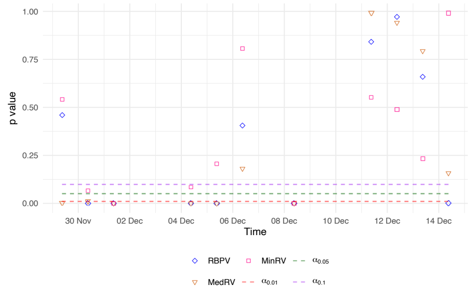
(k) RWEG.DE



(l) TETY.ST



(m) TLW.L



(n) TOTF.DE

Figure A.4: Daily value of $\widehat{G}$ for the brown stocks. The blue points are used when the RBPV is the used jump-robust estimate, the brown-orange points are for MedRV, and the pink points are MinRV. The dashed horizontal lines signify different significance levels; the purple is 10%, the green is 5%, and the red is 1%.