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Abstract

This study examines the stochastic properties of German green and brown stock prices; more specifically, fractional integration methods are applied to daily data on representative green and brown stock indices for the Berlin, Dusseldorf, Frankfurt, Gettex, Munich, and Stuttgart stock exchanges over the period from 13 May 2019 to 8 May 2024. The results indicate a higher degree of persistence in the case of green stock prices vis-à-vis brown ones, although the differences are not statistically significant over the full sample. However, when splitting the sample into three subperiods (pre-Covid-19, Covid-19 and post-Covid-19), statistically significant differences are found, especially during the pandemic period. Moreover, the estimation of a GARCH (1,1) model for stock returns shows that their conditional volatility is characterised by lower persistence and shorter half-lives in the case of brown stocks.

JEL-Codes: C220, G100, Q500.

Keywords: green stocks, brown stocks, fractional integration persistence, Covid-19 pandemic, Germany.

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1. Introduction

ESG (Environment, social, and governance) stands for a set of standards concerning the impact of a business on society and the environment as well as its degree of transparency and accountability. These principles are increasingly being adopted by companies aiming for sustainable investment, environmental considerations being particularly important. Environmentally friendly investments are usually referred to as "green" in contrast to "brown" ones. Practical policy measures for "greening" the economy were first proposed by Pearce et al. (1989), and over the years the United Nations Environment Programme (UNEP) has engaged in several activities contributing to the fight against climate change and providing support for investment in green sectors (UNEP, 2008). An effective way of supporting the green economy and reducing the carbon footprint is to invest in green stocks or bonds issued by companies focusing on environmentally friendly products, services or technologies in sectors such as alternative energy, clean transportation, water management, and waste management (Jian et al., 2011). In fact, since the 2015 Paris Climate Agreement, there have been massive capital inflows into green finance as a result of investors' increasing environmental awareness and preference for environmentally friendly investments (Ferrer et al., 2021).

The European Union (EU) has been particularly active in adopting policies and initiatives aimed at facilitating the transition towards a green economy. More specifically, the Europe 2020 Strategy, launched in 2010, was designed to promote sustainable growth and reduce greenhouse gas emissions, and the European Climate Law (2021) provides the legal framework for achieving climate neutrality by 2050 and the interim goal of reducing emissions by 55% by the year 2030. Interestingly, Germany, namely the biggest EU economy, was initially lagging behind other European countries according to some sustainable investment metrics such as Eurosif; [1] in the GreenMatch survey, Denmark emerged as the greenest country, followed by the United Kingdom and Finland, whilst Germany was ranked 13. [2]

However, more recently, attention in Germany has shifted towards developing green investments to comply fully with ESG principles. The share of green assets in this country relative to brown ones has been going up as a result of environmental considerations as well as of the attractiveness of this type of assets due to their hedging properties; higher demand has pushed their prices up and reduced their expected returns (Pastor et al., 2020). More specifically, the issuance of green bonds by the German government has significantly increased, with the total volume reaching €14.5 billion in 2022, up from €11.5 billion in 2020. This increase reflects the strong demand from investors seeking to support climate protection and sustainability initiatives (Bundesministerium der Finanzen, 2022). Moreover, German utility companies are undergoing a transformative decade, with significant investments in renewable energy and infrastructure to meet the country's ambitious climate goals. These factors have contributed to the higher demand and lower expected returns for green assets, as investors are willing to accept lower financial returns in exchange for the positive environmental and social impact of their investments (S&P Global Ratings, 2024). Therefore, Germany is gradually establishing itself as a leader in green investments, as a result of strong government policies, a commitment to the Paris Agreement, and increasing investor demand for sustainable finance. The country's green investment landscape includes a wide range of instruments such as green stocks, green bonds, and sustainable funds. Despite their benefits, green investments are not without challenges. Market volatility, regulatory changes, and performance risks of green projects can affect the returns on these

[1] https://www.cleanenergywire.org/factsheets/green-and-sustainable-finance-germany
[2] https://www.greenmatch.co.uk/blog/greenest-countries

investments. However, the overall trend has been positive, with growing awareness and demand for sustainable finance driving market growth (S&P Global Ratings, 2024).

Green assets, just like brown ones, can be influenced dramatically by events such as the 2007-2009 global financial crisis and the recent Covid-19 pandemic (Yaya et al., 2021a). For instance, during the latter, stock prices in some developed countries fell by more than 25% within one week (Shehzad et al., 2020). Such events can affect the degree of market efficiency (Ozkan, 2021; Hasan et al., 2021). In an efficient market stock should not be systematically under- or over-valued, and thus investors should earn normal (risk-adjusted) rates of return. Moreover, firms should be able to charge a fair value for their securities. Efficient markets will also allocate resources optimally without the need for central planning, oversight, or government intervention (Chang et al., 2016). It is noteworthy that external shocks such as the Covid-19 pandemic can have different effects on green vis-à-vis brown assets. The reason is that concerns for the environment might take a backseat during a pandemic as countries focus primarily on mitigating the impact of the pandemic. As a result, the popularity of brown assets relative to that of green ones might increase and the relative degree of efficiency of those two markets might also change. On the other hand, during pandemics green assets could become more attractive to investors as safe havens, as shown by Fareed et al. (2022) in the case of the Carbon Efficiency Index (CEI) during the Covid-19 period (see also Haq et al., 2021).

There now exists a sizeable literature analysing the behaviour of green vis-à-vis brown (conventional) assets. Most studies focus on their respective ex-post returns (see, e.g., SSE Initiative, 2017; Chang et al., 2012; Auer and Schuhmacher, 2016; Aswani et al., 2021; Pastor et al., 2021; Luo, 2022; Shackleton et al, 2022; Abu-Ghunmi et al., 2023; Bolton and Kacperczyk. 2022, 2023) or examine the co-movement and price spillover between these two asset classes (see, e.g., Reboredo, 2018; Hammoudeh et al., 2020;

Reboredo and Ugolini, 2020; Yaya et al., 2022; Mensi et al., 2023; Agoraki et al., 2023; Tiwari et al., 2023; Yiming et al., 2024). A common finding is that green assets underperform relative to their brown equivalents (Chang et al. 2012; SSE Initiative, 2017), namely investors tend to pay a price for socially responsible investing (see Auer and Schuhmacher, 2016) as firms with lower ESG scores earn higher returns (Luo, 2022). Further, green growth policies result in investors perceiving a lower risk and thus lead to lower future aggregate stock market returns (Abu-Ghunmi et al., 2023).

One important issue not investigated by the studies discussed above is the degree of persistence of green vis-à-vis brown stock prices and the possibly different impact of the Covid-19 pandemic on their respective stochastic behaviour. The present paper aims to fill this gap in the literature. More specifically, it focuses on the case of Germany which, as already mentioned, has become a leader in green investment in the EU where sustainable growth is being prioritised. The analysis sheds new light on the behaviour of green vis-à-vis stock prices by using fractional integration techniques to examine their persistence, which has implications for the degree of market efficiency. The chosen econometric framework is more general than the standard one based on the dichotomy between stationary I (0) (integrated of order 0) and non-stationary I (1) (integrated of order 1) series since it allows the differencing parameter d to take any real value, including fractional ones. The analysis is carried out using daily data from six of the eight stock exchanges in Germany, namely Berlin, Dusseldorf Frankfurt, Gettex, Munich, and Stuttgart, over the period from 13 May 2019 to 8 May 2024.

The model is also estimated for three subsamples corresponding to the pre-Covid-19, Covid-19 and post-Covid-19 periods to establish whether the behaviour of German green and brown stock prices has changed over time. In addition, we estimate GARCH (1,1) models to examine the conditional volatility of stock returns (a stationary series, unlike stock prices) and their persistence. Therefore, we make a threefold contribution to the literature: we provide new comparative evidence on the persistence of green vis-à-vis stock prices. in the case of Germany, a leading country in the EU, where particular attention is paid to environmental issues; we examine whether the behaviour of these two types of assets has changed over time; we investigate volatility persistence.

The paper is structured as follows: Section 2 describes the data and the methodology, Section 3 presents the empirical results, Section 4 contains some concluding comments.

2. Data and Methodology

We use as representative brown stock indices daily data on the iShares STOXX Europe 600 Oil & Gas UCITS ETF indices which track the performances of companies in the European Oil & Gas sector for the six main stock exchanges in Germany (Berlin, Dusseldorf Frankfurt, Gettex, Munich, Stuttgart). The series span the period from 13 May 2019 to 8 May 2024. The iShares Global Clean Energy UCITS ETF indices for the same six stock exchanges are used instead as representative green stock indices tracking the performance of companies in the global clean energy sector; the sample period is the same as for the brown indices, except for the Berlin series, which spans the period from 17 June 2019 to 8 May 2024. The data source is Bloomberg in all cases.

The empirical framework is based on the concept of fractional integration, with the differencing parameter being allowed to take non-integer values. In particular, the estimated model is the following:

$$y(t) = \alpha + \beta t + x(t), \qquad (1 - L)^d x(t) = u(t), \quad t = 1, 2, \ldots, \qquad (1)$$

where y(t) is the time series under examination; α and β stand for the intercept and the slope coefficient respectively, t denotes a linear time trend, and the detrended series x(t) is assumed to be integrated of order d, where d is an additional parameter to be estimated and L is the lag operator; finally, u(t) is an integrated of order 0 or I(0) process which is assumed in turn to be a white noise or to exhibit autocorrelation. In the latter case we use the exponential spectral method of Bloomfield (1973); this is a non-parametric approach to approximate AR structures with very few parameters which performs fairly well in the context of fractional integration (see, e.g., Gil-Alana, 2004). To examine the stochastic behaviour of the series of interest we carry out Robinson's (1994) tests, which are widely used in empirical applications of fractional integration methods (e.g., Gil-Alana and Robinson, 1997). This method consists of testing the null hypothesis:

$$H_o: \; d \; = \; d_o, \qquad (2)$$

in (1) for any real value d_o, using a Lagrange Multiplier (LM) principle. There are several advantages of this approach compared with other methods. First, d_o may include values outside the stationary region (i.e., $d_o \geq 0.5$) unlike most other procedures that require d_o to be in the stationary range ($d_o < 0.5$); secondly, its limiting distribution is standard normal, which is another distinguishing feature compared with unit root procedures, and this asymptotic behaviour holds even when including deterministic terms as those in Equation (1); finally, it is the most efficient method in the Pitman sense against local departures from the null.

3. Empirical Results

In the following empirical application the time trend coefficient in (1) was found to be statistically insignificant in all cases, and therefore the model was re-estimated with an intercept only. Table 1 and 2 report the results for the original and logged price series respectively in the white noise case. When using the original data (Table 1), although no evidence of mean reversion is found in any single case, higher degrees of integration are generally estimated for the green stock prices. The unit root null hypothesis is rejected in favour of d > 1 in the cases of Frankfurt and Stuttgart for the green stock prices, and the rest of estimates are also above 1, though the unit root null hypothesis (evidence of d = 1) cannot be rejected. However, for the brown stock prices, the estimates of d are in all cases below 1 except for Munich, but even in this case the estimated value is slightly lower than for its green counterpart. The unit root null is not rejected in any case, which supports the efficient market hypothesis (EMH), at least in its weak form (Fama, 1970). The picture based on the log-transformed data (Table 2) is instead more mixed, specifically the estimates of d are lower for the brown stock prices for Dusseldorf, Frankfurt, Gettex and Stuttgart, while they are higher for Berlin and Munich.

INSERT TABLES 1 AND 2 ABOUT HERE

Next, we allow for autocorrelation in the errors. These results are reported in Table 3 and 4 for the original and logged series respectively. In the former case, the estimates of d are lower than under the assumption of white noise errors, although they are all in the I (1) interval, which is again consistent with the EMH. In the latter case there is a slight increase in the order of integration compared to the white noise case only for Berlin, whilst all the other estimates of persistence are slightly lower in the brown markets. In general, higher degrees of persistence are observed in the green stock markets compared with the brown ones.

INSERT TABLES 3 AND 4 ABOUT HERE

Next, we split the sample into three subperiods, namely pre-Covid-19 (Table 5), Covid-19 (Table 6) and post-Covid-19 (Table 7), setting 11 March 2020 as the start and 5 May 2023 as the end of the pandemic respectively (Ashraf, 2020; Coskun et al., 2023), since the former is the date when the World Health Organisation (WHO) characterised the outbreak as a pandemic and the latter is the date when it declared the end to Covid-19 as a global health emergency.[3]

In the pre-Covid-19 period (before 11 March 2020), higher orders of integration are estimated in the green markets than in the brown ones for Frankfurt, Gettex and Stuttgart with both the original and the logged data, although the differences between the two types of markets are not statistically significant since the corresponding confidence intervals do overlap to some extent.

INSERT TABLES 5, 6 AND 7 ABOUT HERE

In the Covid-19 period (11 March 2020 – 5 May 2023), a lower degree of integration is estimated for all brown stock series with both the original and logged values. Moreover, this reduction in the degree of integration is significant in the cases of Dusseldorf, Frankfurt, Gettex and Stuttgart with the original data, and of Dusseldorf, Gettex and Stuttgart with the logged values, since the corresponding confidence intervals do not overlap. In all these cases, mean reversion occurs in the brown stock prices but not in the green ones. Finally, In the post-Covid-19 period (after 5 May 2023), we find lower degrees of persistence in the case of the green stock prices and this difference is statistically significant.

We also investigate volatility persistence by using the Generalised AutoRegressive Conditionally Heteroscedastic (GARCH) model of Bollerslev (1986). Specifically, we estimate the following GARCH(1,1) specification for stock returns (given their stationary nature):

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \qquad (3)$$

[3] https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing---5-may-2023

where α_1 and β_1 are non-negative parameters; ω is a strictly positive constant; r_t stands for the log-returns of stocks, and σ_t^2 is the conditional variance. Persistence is then calculated as $\alpha_1 + \beta_1$, where the closer to 1 this sum is, the more persistent is the volatility of returns. It is also useful to compute the half-life of the effects of shocks, namely the average time it takes for them to halve, which is given by $\ln(0.5)/\ln(\alpha + \beta)$. Thus, the half-life is directly proportional to the degree of persistence of the conditional volatility as measured by $\alpha_1 + \beta_1$ which is always less than 1 in a stationary GARCH (1,1) process.

These results are reported in Table 8. The second column displays all the estimated GARCH parameters, the third the implied degree of persistence, and the fourth the half-lives. It can be seen that all the green stock returns exhibit higher volatility persistence compared to the brown ones, consistently with the fractional integration estimates for the level series. The half-lives imply that in the case of Dusseldorf it takes about 130 days for the effects of shocks to volatility to be halved, the corresponding number of days for Stuttgart being 43. In general, brown stock returns are characterised by shorter half-lives compared to green ones.

INSERT TABLE 8 ABOUT HERE

5. Conclusions

In recent years investors have become significantly more interested in green assets supporting sustainable investment; this reflects their increasing awareness of environmental issues, and also the portfolio diversification opportunities which green assets can offer given their relatively low correlation with other financial assets (see Reboredo, 2018; Reboredo and Ugolini, 2020). As a result, an extensive literature has developed comparing green and brown assets, especially in terms of their profitability (see, e.g., Aswani et al., 2021; Pastor et al., 2021; Shackleton et al, 2022; Bolton and

Kacperczyk. 2022, 2023). However, existing studies have not investigated possible differences between these two types of markets in terms of their degree of persistence, which is a crucial property of asset prices given its implications for market efficiency and policy formulation.

The present study addresses this issue by focusing on representative green and brown stock indices in the case of Germany, a leading country in green investment in the EU, which has been at the forefront of the fight against climate change. It also investigates the possible impact of the Covid-19 pandemic by estimating the model over subsamples as well as the whole sample period. The modelling approach followed is based on the concept of fractional integration, which is more general than and has several advantages over the classical framework only allowing for stationary I (0) and non-stationary I (1) series. The analysis yields a number of new and interesting insights. Specifically, the results indicate a higher degree of persistence in the case of green stock prices vis-à-vis brown ones, although the differences are not statistically significant over the full sample. However, when splitting the sample into three subperiods (pre-Covid-19, Covid-19 and post-Covid-19), statistically significant differences are found. In particular, during the pandemic period the green market appears to have become more efficient relative to the brown one. This presumably reflects a shift in investors' preferences resulting from two contrasting factors: on the on hand, investing in green assets becomes less of a priority during crisis times when the main concern is to reduce the negative impact of exogenous shocks such as the Covid-19 pandemic; on the other hand, demand for such assets as safe havens might increase if financial integration decreases, and thus portfolio diversification opportunities increase, during crisis times. Finally, the estimation of a GARCH (1,1) model for stock returns shows that their conditional volatility is characterised by lower persistence and shorter half-lives in the case of brown stocks.

Future work should extend the analysis to other countries to obtain wider evidence on possible differences in the degree of persistence and market efficiency of green vis-à-vis stock prices. From a modelling point of view, other approaches such as recursive or rolling window estimation could be used in order to allow for the possibility of a gradual evolution over time of the parameters of interest. Further, possible nonlinearities could be examined by using, for example, orthogonal polynomials in time as in Hamming (1973) and Bierens (1997) in the context of fractional integration as in Cuestas and Gil-Alana (2016), or Fourier functions in time as in Gil-Alana and Yaya (2021), or neural networks as in Yaya et al. (2021b).

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Table 1: Estimated coefficients. Original data. White noise errors

	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.01 (0.97, 1.06)	5.5802 (24.70)	0.99 (0.95, 1.04)	32.1928 (65.54)
DUSSELDORF	1.03 (0.99, 1.07)	5.1112 (26.03)	0.99 (0.95, 1.03)	32.2442 (65.98)
FRANKFURT	1.04 (1.00, 1.09)	5.0111 (25.99)	0.99 (0.95, 1.03)	32.2768 (64.04)
GETTEX	1.03 (0.99, 1.08)	5.0275 (26.18)	0.97 (0.93, 1.01)	32.3529 (63.66)
MUNICH	1.03 (0.99, 1.08)	5.1385 (26.35)	1.02 (0.99, 1.08)	32.2054 (70.04)
STUTTGART	1.04 (1.00, 1.09)	5.0169 (26.43)	0.97 (0.93, 1.01)	32.2143 (64.01)

Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report the estimates of the intercept with the corresponding t-values in brackets.

Table 2: Estimated coefficients. Logged data. White noise errors

	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.00 (0.96, 1.05)	1.7191 (73.29)	1.02 (0.98, 1.06)	3.4710 (187.10)
DUSSELDORF	1.03 (0.99, 1.07)	1.6314 (83.34)	1.00 (0.96, 1.05)	3.4793 (186.09)
FRANKFURT	1.02 (0.98, 1.06)	1.6126 (79.57)	1.01 (0.97, 1.06)	3.4737 (187.94)
GETTEX	1.03 (0.99, 1.07)	1.6149 (82.11)	0.99 (0.95, 1.03)	3.4763 (182.79)
MUNICH	1.01 (0.97, 1.05)	1.6366 (79.52)	1.06 (1.02, 1.11)	3.4715 (202.91)
STUTTGART	1.03 (0.99, 1.07)	1.6129 (81.85)	0.97 (0.93, 1.01)	3.4724 (177.82)

Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report the estimates of the intercept with the corresponding t-values in brackets.

Table 3: Estimated coefficients. Original data. Autocorrelated errors

	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	0.96 (0.91, 1.03)	5.5801 (24.76)	0.94 (0.89, 1.02)	32.2281 (65.89)
DUSSELDORF	1.00 (0.95, 1.07)	5.1114 (25.37)	0.97 (0.92, 1.04)	32.2447 (66.04)
FRANKFURT	0.99 (0.94, 1.06)	5.0178 (26.02)	0.97 (0.91, 1.04)	32.2890 (64.92)
GETTEX	1.02 (0.97, 1.09)	5.0289 (26.19)	0.97 (0.90, 1.04)	32.3524 (63.64)
MUNICH	0.99 (0.94, 1.05)	5.1365 (26.35)	0.97 (0.91, 1.04)	32.2455 (70.25)
STUTTGART	1.01 (0.95, 1.08)	5.0198 (26.42)	0.97 (0.91, 1.04)	32.2148 (64.03)

Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report the estimates of the intercept with the corresponding t-values in brackets.

Table 4: Estimated coefficients. Logged data. Autocorrelated errors

	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	0.96 (0.90, 1.03)	1.7193 (73.48)	0.98 (0.92, 1.05)	3.4719 (187.34)
DUSSELDORF	1.02 (0.96, 1.08)	1.6314 (83.31)	1.01 (0.95, 1.08)	3.4793 (186.11)
FRANKFURT	1.02 (0.96, 1.09)	1.6121 (79.59)	1.01 (0.93, 1.08)	3.4738 (187.93)
GETTEX	1.04 (0.98, 1.09)	1.6147 (82.16)	1.00 (0.94, 1.07)	3.4760 (182.80
MUNICH	1.03 (0.96, 1.08)	1.6368 (79.59)	1.01 (0.94, 1.08)	3.4725 (202.62
STUTTGART	1.02 (0.97, 1.09)	1.6139 (81.83)	1.01 (0.95, 1.08)	3.4716 (177.80)

Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report the estimates of the intercept with the corresponding t-values in brackets.

Table 5: Estimated coefficients. Pre-Covid-19 period

i) Original data. White noise errors				
	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.02 (0.83, 1.29)	5.5811 (28.09)	1.06 (0.97, 1.17)	32.1453 (66.94)
DUSSELDORF	1.11 (1.00, 1.26)	5.1134 (58.31)	1.14 (1.04, 1.27)	32.4132 (70.91)
FRANKFURT	1.14 (1.01, 1.29)	5.0028 (54.33)	1.10 (1.01, 1.21)	32.2213 (70.47)
GETTEX	1.20 (1.06, 1.38)	5.0157 (58.55)	1.08 (0.99, 1.19)	32.2933 (68.27
MUNICH	1.01 (0.90, 1.15)	5.1379 (49.89)	1.14 (1.04, 1.26)	32.1427 (71.76)
STUTTGART	1.18 (1.05, 1.35)	5.0065 (56.85)	1.02 (0.91, 1.33)	32.1838 (67.18)
ii) Logged data. White noise errors				
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.00 (0.81, 1.26)	1.7198 (54.30)	1.05 (0.96, 1.16)	3.4704 (193.45)
DUSSELDORF	1.08 (0.97, 1.22)	1.6312 (115.26)	1.15 (1.05, 1.27)	3.4781 (204.94)
FRANKFURT	1.12 (0.99, 1.27)	1.6109 (108.71)	1.11 (1.01, 1.21)	3.4723 (206.27)
GETTEX	1.17 (1.03, 1.34)	1.6127 (116.95)	1.06 (0.97, 1.17)	3.4756 (194.20)
MUNICH	0.98 (0.87, 1.07)	1.6366 (98.95)	1.15 (1.05, 1.28)	3.4709 (210.74)
STUTTGART	1.14 (1.01, 1.31)	1.6119 (112.20)	0.98 (0.88, 1.08)	3.4726 (190.72)

Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report the estimates of the intercept with the corresponding t-values in brackets.

Table 6: Estimated coefficients. Covid-19 period

i) Original data				
	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.00 (0.95, 1.06)	5.9290 (19.36)	0.94 (0.88, 1.01)	20.9495 (39.58)
DUSSELDORF	**1.02 (0.97, 1.08)**	**5.6125 (24.79)**	**0.91 (0.86, 0.96)**	**20.0505 (30.21)**
FRANKFURT	**1.04 (0.99, 1.10)**	**5.6867 (25.13)**	**0.92 (0.87, 0.98)**	**20.2445 (38.35)**
GETTEX	**1.03 (0.98, 1.08)**	**5.4929 (24.18)**	**0.90 (0.84, 0.96)**	**20.0089 (36.91)**
MUNICH	1.03 (0.98, 1.09)	5.8287 (25.27)	0.98 (0.92, 1.04)	20.4297 (41.92)
STUTTGART	**1.03 (0.98, 1.09)**	**5.5412 (24.52)**	**0.90 (0.85, 0.98)**	**19.9805 (37.34)**
ii) Logged data. White noise errors				
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	0.98 (0.93, 1.03)	1.5968 (64.67)	0.96 (0.90, 1.03)	3.0224 (148.23)
DUSSELDORF	**1.01 (0.96, 1.03)**	**1.7228 (78.14)**	**0.92 (0.87, 0.95)**	**2.9982 (144.88)**
FRANKFURT	1.00 (0.96, 1.06)	1.7334 (76.95)	0.96 (0.90, 1.02)	3.0122 (147.49)
GETTEX	**1.01 (0.97, 1.05)**	**1.7008 (77.04)**	**0.91 (0.86, 0.96)**	**2.9967 (143.78)**
MUNICH	0.99 (0.95, 1.05)	1.7586 (76.32)	0.98 (0.91, 1.04)	3.0052 (159.33)
STUTTGART	**0.99 (0.96, 1.05)**	**1.7086 (76.63)**	**0.89 (0.85, 0.95)**	**2.9910 (140.14)**

Note: Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report the estimates of the intercept with the corresponding t-values in brackets. In bold, the cases where statistically significant differences are found in the order of integration of brown vis-à-vis green markets as the confidence intervals do not overlap.

Table 7: Estimated coefficient. Post-Covid-19 period

i) Original data				
	Green Stock Market Prices		Brown Stock Market Prices	
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.02 (0.94, 1.14)	9.6827 (88.92)	0.87 (0.78, 0.97)	34.3678 (91.97)
DUSSELDORF	1.01 (0.92, 1.12)	9.6329 (86.40)	0.91 (0.83, 1.03)	34.3908 (98.08)
FRANKFURT	0.94 (0.86, 1.04)	9.6342 (77.57)	0.87 (0.79, 0.97)	34.6405 (98.10)
GETTEX	0.96 (0.88, 1.07)	9.7196 (82.87)	0.88 (0.80, 0.99)	34.4445 (93.81)
MUNICH	1.00 (0.91, 1.10)	9.6687 (85.06)	0.92 (0.84, 1.03)	34.4213 (97.73)
STUTTGART	1.03 (0.94, 1.13)	9.6542 (89.45)	0.92 (0.83, 1.03)	34.3864 (98.21)
ii) Logged data. White noise errors				
Series	d (95% interval)	Intercept (tv)	d (95% interval)	Intercept (tv)
BERLIN	1.03 (0.93, 1.15)	2.2707 (165.91)	0.87 (0.79, 0.97)	3.5371 (335.94)
DUSSELDORF	1.01 (0.92, 1.13)	2.2654 (16.104)	0.91 (0.83, 1.03)	3.5378 (357.23)
FRANKFURT	0.93 (0.85, 1.04)	2.2655 (144.76)	0.87 (0.78, 0.97)	3.5446 (335.61)
GETTEX	0.97 (0.89, 1.08)	2.2746 (156.57)	0.88 (0.80, 0.99)	3.5392 (343.21)
MUNICH	0.99 (0.90, 1.10)	2.2689 (157.88)	0.92 (0.83, 1.03)	3.5374 (358.20)
STUTTGART	1.03 (0.94, 1.15)	2.2671 (166.89)	0.91 (0.83, 1.02)	3.5386 (355.58)

Note: Note: Columns 2 and 4 report the estimates of d with the corresponding confidence intervals in brackets, whilst columns 3 and 5 report estimates of the intercept with the corresponding t-values in brackets.

Table 8: Estimates of volatility persistence in green and brown stock returns

Green Stock Market Returns	**GARCH estimates** $(\omega, \alpha_1, \beta_1)$	**Persistence** $\alpha_1 + \beta_1$	**Half-life**
Berlin	6.37E-06, 0.1069, 0.8853	0.9922	88.5
Dusseldorf	3.60E-06, 0.0919, 0.9028	0.9947	130.4
Frankfurt	4.51E-06, 0.0771, 0.9143	0.9914	80.3
Gettex	4.76E-06, 0.0883, 0.9017	0.9900	69.0
Munich	5.67E-06, 0.0716, 0.9169	0.9885	59.9
Stuttgart	6.70e-06, 0.0994, 0.8847	0.9841	43.2
Brown Stock Market Returns	**GARCH estimates** $(\omega, \alpha_1, \beta_1)$	**Persistence** $\alpha_1 + \beta_1$	**Half-life**
Berlin	1.32E-05, 0.1125, 0.8458	0.9583	16.3
Dusseldorf	8.36E-06, 0.1171, 0.8600	0.9771	29.9
Frankfurt	8.91E-06, 0.0614, 0.9168	0.9782	31.4
Gettex	1.02E-05, 0.1277, 0.8442	0.9719	24.3
Munich	9.63E-06, 0.1074 0.8604	0.9678	21.2
Stuttgart	8.45E-06, 0.1207, 0.8559	0.9766	29.3

Note: Column 2 reports the estimates of the GARCH(1,1) parameters, column 3 the estimated degree of persistence, and column 4 the corresponding half-lives.