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The effect of overconfidence behaviour on stock market volatility in Belgium

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Abstract. *The purpose of this paper is to measure whether the investor operating on the Brussels Stock Exchange exhibits overconfidence behaviour, and to examine, under this hypothesis, the role of overconfidence in explaining fluctuations in the value of the BEL20 benchmark index over a 22-year period from 03 January 2000 to 21 October 2022. By exploiting econometric techniques in terms of causality and modelling conditional volatility, the results of this research show the presence of the excess confidence feature and its positive effect on the conditional volatility of the daily return of the BEL20 index.*

Keywords: excess confidence, volatility, stock returns, volume, GJR-GARCH.

JEL Classification: D01, G41.

Introduction

According to the teachings of the informational efficiency hypothesis of financial markets (Fama, 1970), prices should not deviate extremely from fundamentals, this implies that bubbles should not occur, and that price volatility is kept at reasonable levels. However, the financial literature reveals that markets are sometimes excessively volatile. Indeed, Shiller (1981) shows that the volatility of real prices largely exceeds that of the prices anticipated ex-post by the discount model of future flows and in particular the dividend discount model (DDM). This excessive volatility cannot be explained by the evolution of fundamentals, such a conclusion opened the debate on the explanatory factors of excessive volatility. In this context, work carried out in the field of cognitive psychology has integrated psychological factors to explain the behaviour of stock prices. The results of this research have given rise to a school of thought in finance that introduces investor sentiment as a component of asset prices. The consideration of market sentiment refers to behavioural finance, which has identified a set of behavioural biases that can describe the mechanisms of price formation, thus providing some answers as to the nature of volatility, and in particular those that account for the spectacular nature of stock market fluctuations.

The financial literature reveals that investor overconfidence is one of the most documented behaviours that explain the nature and origin of price volatility, especially when it reaches critical levels. The relationship between overconfidence and volatility is materialized through the frequency and intensity of trading, referring to the volume of transactions. Indeed, according to Gervais and Odean (2001), overconfident investors opt for aggressive strategies by increasing the frequency of trading. This relationship has been addressed by a large body of literature, whose main results converge towards a positive relationship between volatility and the level of trading on a market. In addition, work in this same context consists of introducing the past returns of security as explanatory variables of the current trading volume (Glaser and Weber, 2009), as it is believed that investors motivated by past gains tend to increase their trading activity of securities.

The positive link between overconfidence and trading volume on the one hand, and between past returns, volume and volatility on the other, explains the use of techniques for modelling volume and the return series in an autoregressive environment by integrating the past values of the explanatory and dependent variables, and by studying the link and the direction of causality between these variables. Then, the volume of transactions is introduced into a model of the conditional volatility of returns by taking into account the heteroscedastic and asymmetric character of the series of price returns. These different techniques make it possible, on the one hand, to measure excess confidence through the causal link between past returns and trading volume and, on the other hand, to examine whether excess confidence, as a component of volume, has any explanatory power for the conditional volatility of returns.

The purpose of this paper is to provide a measure of Belgian investors' overconfidence and to study the role of possible overconfidence behaviour in explaining the excessive volatility of the BEL20 index return series. The present work will be organized as follows, in the first section we will present the nature and origin of investor overconfidence and its relation to excessive volatility. The second section will be devoted to the empirical literature on the measurement of overconfidence, and the introduction of trading volumes in a GARCH-type model (or one of its extensions) to examine the link between overconfidence and volatility. The third section will present the methodology protocol adopted. Finally, the last section will be devoted to the main results of the various empirical tests.

1. Rationale for the relationship between excessive volatility and overconfidence

Excessive volatility, which refers to a strong deviation of prices from their fundamentals, has been highlighted as a financial anomaly since 1981 following the work of Shiller, then LeRoy and Porter. Shiller's pioneering work consisted in comparing the volatility, measured by the standard deviation, of the Standard & Poors Composite Index (S&P500) with that of the ex-post values anticipated by the Dividend Discount Model (DDM) for the period from 1871 to 1979. Shiller's conclusions were in favour of a significant gap between actual prices and the fundamental values rationally anticipated by the DDM. This test, known as the "bounds of variance" test, was then applied to several financial markets to show, in many cases, the violation of the dividend discount model. The DDM states under the assumption of informational efficiency that prices gravitate around fundamental values, and that financial bubbles should not occur in an informationally efficient market. Shiller's classic excessive volatility test has been subject to various criticisms. These criticisms concern in particular the non-stationarity of the price and dividend series, and the instability of the interest rate, introduced as the discount rate for flows in the MDD (Arbulu and Fontaine, 1998; Flavin, 1983). As a result of these limitations, studies carried out towards the end of the 1980s took into consideration the development of econometric techniques, and in particular, those based on the cointegration method with reference to the work of Engle and Granger (1987). The cointegration study thus makes it possible to examine the long-term relationship between prices and dividends as a test of volatility and informational efficiency. In this sense, a number of studies have shown a long-lasting gap between dividends and prices, thus contradicting the myth of fundamental value, and leaving the debate open as to the explanations for the strong market turbulence. In this respect, how can critical levels of volatility be explained? And if the predictions of financial theory are no longer sufficient to account for the true values of assets, what is the appropriate theoretical framework to explain the spectacular movements in stock prices and stock market indices?

Empirical studies reveal that excessive volatility cannot be explained by rational arguments alone. The limitations of explanations from classical financial theory make it legitimate to resort to other explanations, including those from the behavioural stream of finance. This complementary approach originates in the work of cognitive psychology. Indeed, following the work of Kahneman and Tversky (1974, 1979), the psychology of the investor is now one of the factors to be taken into consideration in order to understand how investment decisions are influenced in a risky environment such as the stock market. Certain behavioural biases are therefore taken into account to understand the mechanisms of price formation, and the impact of financial anomalies as irregularities observed in the financial markets that run counter to the hypothesis of informational efficiency. Regarding the abnormal nature of stock market volatility, research in behavioural finance considers that critical levels of volatility are due to investors' overconfidence (Odean, 1999; Hirshleifer and Luo, 2001; Gervais and Odean, 2001; Glaser and Weber, 2009).

According to Bessière (2007), an individual's overconfidence refers to a situation of overconfidence in his or her own skills and knowledge. This behaviour is reflected in an overweighting of private information over public information. Furthermore, the literature states that overconfidence worsens in situations of uncertainty.

Indeed, when it comes to making choices or assessments in a risky world, individuals tend to overestimate their own opinions while ignoring other information that may be relevant. Overconfidence leads individuals to underestimate the risk inherent in securities traded in financial markets. This leads to under-diversified portfolios and increased volatility (Skata, 2008). Other researchers come to the same conclusion regarding the effect of overconfidence on the level of volatility, Chuang and Lee (2006) state that overconfident investors tend to neglect risk, which fuels the level of volatility. Now, if excessive volatility can be explained by the behaviour of the overconfident investor, how can such behaviour be measured? And how can we relate overconfidence to volatility?

2. Measuring overconfidence and its impact on volatility

In this section, we present a measure of overconfidence based on researchers' findings and then show the contribution of econometric modelling in explaining the conditional volatility of equity market returns by introducing overconfidence, as a component of trading volume, into the volatility model.

2.1. Measuring overconfidence

To measure the overconfidence of investors operating in a financial market, a large literature has developed around a positive relationship between past returns and current trading volume. According to Odean (1998), overconfident investors tend to trade securities excessively. This result was confirmed by Gervais and Odean (2001) and Statman et al. (2006). The study by Chuang and Lee (2006) and Glaser and Weber (2009) confirm that market gains are a source of motivation for overconfident investors to develop aggressive behaviour towards trading activities in the market.

The study of the link between past returns and trading volume uses the bivariate causality test of Granger (1969, 1988) or Toda-Yamamoto (1995) depending on the stationarity test. The causality test from lagged returns to the current trading volume would therefore be a measure of overconfidence that has been adopted to show such behaviour in developed financial markets. For emerging market financial centres, the same approach has been used to detect this behavioural bias in the markets of Tunisia (Naoui and Khaled, 2010), Egypt (Metwally and Darwish, 2015) and more recently in the Pakistani market (Zia et al., 2017). The study of the link between trading volume and past returns is therefore based on Vector Autoregressive (VAR) modelling extended by a Granger or Toda-Yamamoto causality test. According to Chuang and Lee (2006), this involves conducting a causality test between returns and trading volume with the following specification:

$$V_t = \alpha_{11} + \sum_{j=1}^{p} \beta_{11j} V_{t-j} + \sum_{j=1}^{p} \beta_{12j} R_{m,t-j} + \varepsilon_{1t} \quad (1)$$

$$R_{m,t} = \alpha_{21} + \sum_{j=1}^{p} \beta_{21j} V_{t-j} + \sum_{j=1}^{p} \beta_{22j} R_{m,t-j} + \varepsilon_{2t} \quad (2)$$

V_t: Volume of market transactions at time t;
V_{t-j}: Volume of delayed transactions;
$R_{m,t}$: Current market returns t;
$R_{m,t-j}$: Delayed market returns;
p: Optimal number of delays.

In a VAR environment, the answer to the question of the direction of causality from returns to trading volume only takes into account the first specification as the literature provides evidence of overconfident behaviour when overconfident investors base their current level of activity on past returns. Now if the measure of overconfidence is obtained by examining the direction of causality in question, how can we examine the impact of such behaviour on the level of volatility?

2.2. Link between overconfidence and volatility

If overconfidence assumes that current volume is explained by past returns, volatility, measured by the dispersion of returns, assumes that trading volume explains these fluctuations. However, in order to know whether overconfidence will have explanatory power for volatility, the empirical literature reveals the importance of decomposing trading volume into two components as follows:

$$V_t = \alpha + \sum_{j=1}^{p} \beta_j R_{j-t} + \varepsilon_t \quad (3)$$

$$V_t = \left[\sum_{j=1}^{p} \beta_j R_{j-t}\right] + [\alpha + \varepsilon_t] \quad (4a)$$

$$V_t = Overconfidence_t + Non - overconfidence_t \quad (4b)$$

To examine the role of trading volume, and more specifically the role of its component related to overconfidence requires a volatility model. The financial literature shows that the characteristics of the distributions of returns impose the introduction of the two components of the volume of transactions in a generalised conditionally heteroscedastic autoregressive GARCH (p, q) model developed by Bollerslev (1986), or one of its extensions. GARCH (p,q) models belong to the ARCH (autoregressive conditional heteroscedastic) type models where the conditional variance depends on the squares of past innovations (residuals).

Indeed, it is a modelling of the squares of the residuals from a constrained ARMA (Autoregressive moving average model). Volatility modelling, based on GARCH-type models, has undergone considerable development since the 1990s given the impact of negative and positive innovations on volatility. This was materialised by the introduction of models such as EGARCH (Exponential GARCH) by Nelson (1991), the AGARCH (Asymmetric GARCH) model by Engle (1990), or threshold models such as the Threshold GARCH model (TGARCH) introduced by Zakoian (1994).

The empirical literature on overconfidence reveals the importance of introducing the two components of trading volume, according to equation (4b) in a GARCH-type volatility model of the return series or one of its extensions (Benos, 1998; Chuang and Lee, 2006; Abbes et al., 2009; Naoui and Khaled, 2010).

The purpose of this study is to show the contribution of overconfidence in explaining the volatility of the Belgian financial market by exploiting econometric techniques developed in the same way as previous studies. This is done by first measuring the excess confidence of the Belgian investor, before introducing the two components of the volume of transactions in a GARCH-type model or one of its extensions above.

3. Study of the impact of overconfidence on the volatility of the Belgian financial market

The purpose of this section is to measure and study the impact of overconfidence on the volatility of the Brussels Stock Exchange benchmark index.

3.1. Methodology

To examine the contribution of overconfidence in explaining volatility, and in particular the observed deviations from fundamentals, we conduct this study over a 22-year period, from 03 January 2000 to 21 October 2022. Our data is available on the official investing.com website and includes daily values of the BEL20 index of the Brussels stock exchange in Belgium, and market trading volume. From this data we build the return and volume series as follows:

$Rt\_m = ln(p_t/p_{t-1}) \times 100$ is the daily market return of the BEL20 index, p_t et p_{t-1} respectively the values of the index in t and $t-1$.

$Rt\_vol = ln(V_t/V_{t-1}) \times 100$ is the daily return on trading volumes, V_t et V_{t-1} respectively the volumes of market transactions in t and $t-1$.

The two series of BEL20 index returns (Rt_m) and trading volumes (Rt_vol) constitute the variables of our empirical test (see figures A1, A2, A3 and A4, in the appendices, for the evolution of the BEL20 index prices, trading volumes and their returns).

Before starting our empirical investigation, we tested the stationarity of the selected series with the Augmented Dickey-Fuller ADF test (1981). The measure of overconfidence is a bivariate causality test with Granger, and subject to a possible causality from past returns to the current volume, the overconfidence as a hypothesis will be accepted. Secondly, the presence of such a behavioural bias implies modelling volatility by introducing trading volumes into a GARCH-type model or one of its extensions studied in the literature on overconfidence. However, the examination of the impact of the confidence effect requires a decomposition of the trading volume according to equation (4b). The estimation of the parameters of equation (4b) is therefore a step before introducing the overconfidence (OVER) and non-overconfidence (NONOVER) components into a GARCH model.

As in previous work, the asymmetric effect of positive and negative shocks on the index return requires the use of models such as EGARCH (Nelson, 1991), GJR-GARCH

(Glosten et al., 1993) or the TGARCH model (Zakoian, 1994). To examine the effect of overconfidence on the conditional volatility of market profitability, we propose a GJR-GARCH (1,1) model as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 I_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \eta_1 OVER + \eta_2 NONOVER \quad (5)$$

σ_t^2: The conditional variance at date t;

$\omega, \alpha_1, \gamma_1, \beta_1, \eta_1, \eta_2$: The parameters of the model to be estimated;

I_{t-1}: A dummy variable, si $\varepsilon_{t-1} < 0$ then $I_{t-1} = 1$, otherwise $I_{t-1} = 0$;

OVER: The overconfidence component of volume;

NONOVER: The volume component not related to overconfidence.

The specification of the conditional variance according to equation (5) incorporates a dummy variable (I_{t-1}) that takes the value 1 if the lagged innovation ε_{t-1} is negative, and the value 0 otherwise. Thus, when γ_1 is positive, this indicates that volatility will increase more strongly following a negative shock or negative innovation than following a positive shock.

To examine the effect of overconfidence on the conditional volatility of the market return, it must be significantly positive. Recall that a positive relationship between OVER and conditional volatility has been demonstrated in previous studies (Karpoff, 1987; Chuang and Lee, 2006; Statman et al., 2006).

4. Results of the various empirical investigations

Before presenting the results of the estimations, we will present a first descriptive analysis.

4.1. Descriptive statistics

For the two sets of returns that we have chosen for our study, Table 1 below provides the main characteristics of the two distributions.

Table 1. *Descriptive statistics of the variables studied*

	Rt_m	Rt_vol
Number obs.	5835	5835
Mean	0.0006	0.0101
Median	0.0347	0.1982
Maximum	9.3339	204.6218
Minimum	-15.3275	-233.0429
Std-deviation	1.2564	35.2552
Skewness	-0.3860	-0.1000
Kurtosis	12.5087	7.0618
Jarque-Bera	22127.31 (0.0000)	4020.979 (0.0000)

Note: The values in brackets represent the p-values associated with the Jarque-Bera statics.
Source: Authors, based on BEL20 daily returns and trading volumes.

For normally distributed series, the skewness and kurtosis coefficients are equal to 0 and 3 respectively. Both series have Skewness different from 0 and negative. The Kurtosis coefficients are greater than 3. We are thus in the presence of leptokurtic distributions that have thick tails compared to the extremities of a normal distribution. These observed characteristics finally give a distribution different from the normal distribution (see figures A5 and A6 in the appendices), which is confirmed by the Jarque-Bera statistic (0.0000 less than 0.05). All this corroborates a large body of literature which shows that financial series are not normal but leptokurtic and asymmetric.

Table 2. *Correlation matrix of the variables studied*

	Rt_vol	Rt_m
Rt_vol	1.0000	
Rt_m	-0.0486 (0.0002)	1.0000

Note: The value in brackets represents the p-value associated with the correlation coefficient.
Source: Authors, our estimates.

There is a negative and significant correlation at the 5% level between the BEL20 index return series (Rt_m) and the trading volume series (Rt_vol). Moreover, this correlation coefficient is between -0.75 and 0.75. This indicates that there is no multicollinearity between the variables. Therefore, all these variables can be analysed together.

4.2. Measuring overconfidence

Before examining the relationship between past returns and current trading volumes, we test the stationarity of the two series selected, the series of daily market returns of the BEL20 index noted Rt_m and the series of daily returns of trading volumes (Rt_vol) (see methodology). According to Table 3 below, both series are stationary in level, this does not imply any transformation to make them stationary.

Table 3. *Results of the Augmented Dickey-Fuller (ADF) stationarity tests*

Model tested	*Rt_m*	*Rt_vol*	Decision
Model [3]: with constant and trend	-72.1449 (0.0000) [-3.9596]	-24.5310 (0.0000) [-3.9596]	Stationary
Model [2]: with constant without trend	-72.1501 (0.0001) [-3.4312]	-24.5219 (0.0000) [-3.4312]	Stationary
Model [1]: without consistency or trend	-72.1562 (0.0001) [-2.5653]	-24.5235 (0.0000) [-2.5653]	Stationary

Note: The values in brackets represent the p-values associated with the augmented Dickey-Fuller statistics. The values in square brackets are the critical values of the test statistics at the 1% threshold.
Source: Authors, our estimates.

According to Table 3, both series of market returns and trading volume returns are stationary at level (I(0)). We therefore continue our analysis with a bivariate causality test using the Granger causality test in the sense of Toda-Yamamoto (1995) as our series are stationary at level (I (0)), this requires first determining the optimal number of lags of the VAR model (equation 1 and 2). According to the criteria for selecting the number of lags (Table 4 below), we choose the number 9 to conduct our causality test.

Table 4. *Selection of the optimal number of lags in the VAR model*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-38596.28	-	1952.514	13.25263	13.25492	13.25342
1	-38157.20	877.6986	1681.583	13.10325	13.11012	13.10563
2	-37962.15	389.7627	1574.818	13.03765	13.04910	13.04163
3	-37886.44	151.2513	1536.514	13.01303	13.02906	13.01860
4	-37790.37	191.8344	1488.703	12.98141	13.00203	12.98858
5	-37783.05	14.62400	1487.004	12.98027	13.00546	12.98903
6	-37764.92	36.17181	1479.809	12.97542	13.00519	12.98578
7	-37748.46	32.82466	1473.495	12.97115	13.00550	12.98309
8	-37728.16	40.48878	1465.270	12.96555	13.00448	12.97909
9	-37687.61	80.84193*	1446.995	12.95300	12.99651*	12.96813*
10	-37683.01	9.170459	1446.696*	12.95279*	13.00088	12.96952

Note: For each criterion the sign (*) indicates the optimal number of delays obtained.
Source: Authors, our estimates.

Granger causality in the sense of Toda-Yamamoto (1995) is used to examine the direction of the relationship between market returns and trading volume returns. Table 5 below shows the result of the causality test according to equations (1) and (2) representative of this test.

Table 5. *Granger causality test in the Toda-Yamamoto sense between trading volumes and market returns (number of lags = 9)*

Dependent variable: Rt_vol			
Exclued	Chi-sq	df	Prob.
Rt_m	58.18487*	9	0.0000
All	58.18487*	9	0.0000
Dependent variable: Rt_m			
Exclued	Chi-sq	df	Prob.
Rt_vol	11.86645	9	0.2209
All	11.86645	9	0.2209

Note: (*) indicator of significance at the 1% level.
Source: Authors, our estimates.

Table 5 shows that the market returns variable (Rt_m) causes the trading volumes variable (Rt_vol) at the 1% threshold (p-value = 0.0000). This implies the presence of overconfidence behaviour in line with the findings of previous research.

4.3. Introduction of trading volumes in a conditional volatility model

The conditional modelling of the volatility of the daily market returns of the BEL20 index (Rt_m) first passes through an ARCH effect test, then a model of the GARCH family of which we have retained the GJR-GARCH (1,1) model will be used for the estimations.

Table 6. *ARCH test results for daily market returns of the BEL20 index*

RESID^2	Coeff.	Std. Error	t.-Stat	p-value
C	1.2825	0.0716	17.9050	0.0000
RESID^2(-1)	0.1820	0.0128	14.1427	0.0000
F-statistic: 200,0162 p-value: 0.0000. Obs. *R-squared: 193.4491 p-value: 0.0000.				

Source: Authors, our estimates.

The results of the ARCH test of the daily market returns of the BEL20 index show us that the autoregressive coefficient associated with the lagged (RESID^2(-1)) squared residuals is positive and significantly different from zero. There is thus a presence of conditional heteroscedasticity in the return series. In addition, we find that the probability associated with the test statistic TR^2 (Obs*R-squared) is zero: we therefore reject the null hypothesis of homoscedasticity in favour of the alternative of conditional heteroscedasticity. In order to take into account this ARCH effect, our objective is now to estimate the variance equation. We will use the GJR-GARCH model for this purpose. The results of the estimations of the GJR-GARCH (1,1) model using the GED (Generalized Error Distribution) are given in Table 7 below.

Table 7. *Estimation results of the GJR-GARCH (1,1) model with the GED law*

GJR-GARCH (1,1)		
Parameters	Coefficients	p-values
ω	0.5357*	0.0000
α_1	0.0807*	0.0009
γ_1	0.2755*	0.0000
β_1	0.4910*	0.0000
η_1	0.0370**	0.0160
η_2	0.0058*	0.0000
GED Parameter	1.1415*	0.0000
Log Likelihood	*-8509.140*	-
AIC	*2.9201*	-
SIC	*2.9304*	-
HQ	*2.9237*	-

Note: (*), (**) indicator of significance at the 1% and 5% level respectively.
AIC: Akaike information criterion, SIC: Schwarz information criterion and HQ: Hannan-Quinn information criterion.
Source: Authors, our estimates.

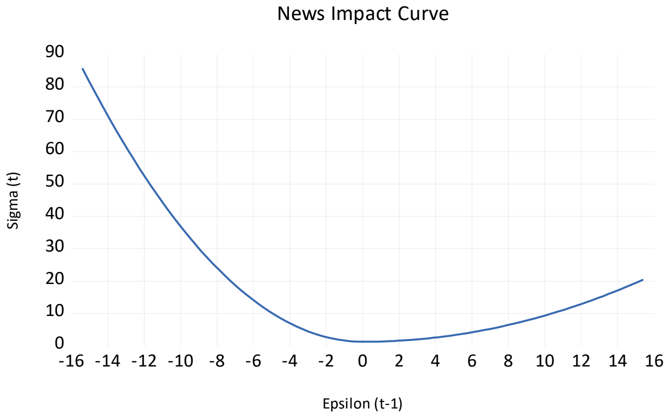
Table 7 shows that the coefficient of the parameter (η_1) associated with the overconfidence variable ($OVER$) is positive and significant at the 5% level, indicating the positive impact of overconfidence on the conditional volatility of Belgian stock market returns.

This is because when investors are optimistic, they tend to overestimate the accuracy of the information in their possession and speculate more on the stock market. They are therefore overconfident and buy even the riskiest financial securities. As a result, the purchases of financial securities become greater than the sales. This leads to a rise in stock market prices, which form speculative bubbles. Since prices cannot rise indefinitely, speculative bubbles burst, leading to the collapse of financial asset prices and even financial crises. The collapse of financial asset prices thus increases volatility because, according to Black (1976), there is an inverse (asymmetric) relationship between stock prices (or their returns) and volatility. This asymmetric phenomenon between stock prices and volatility has been carefully presented in the stylized facts (graphs) of Anzian's (2022) article.

The other coefficient of the parameter (η_2) associated with non-excess confidence ($NONOVER$) is also positive and significant at the 1% level indicating that the other component of trading volume, unrelated to investor overconfidence, also has a part in explaining volatility. For the other parameters of the model, α_1 and β_1 are positive and significant at the 1% level, so we accept that the conditional variance is explained by the square of the lagged residual and by the lagged variance. The coefficient of the GED law parameter being significant at the 1% threshold and less than 2, this means that the normal law should not be used to carry out the estimations because we are very far from normality. This is why we used a distribution law whose tail is thicker than that of the normal law (the GED law in our case). This would make it possible to take into account extreme events and shocks that have a large magnitude. The coefficient of the skewness parameter (γ_1) is positive and significant at the 1% level, which implies that a negative shock to returns increases volatility significantly.

The asymmetry can be visualised by the news impact curve below:

Figure 1. *The information impact curve of the GJR-GARCH model*

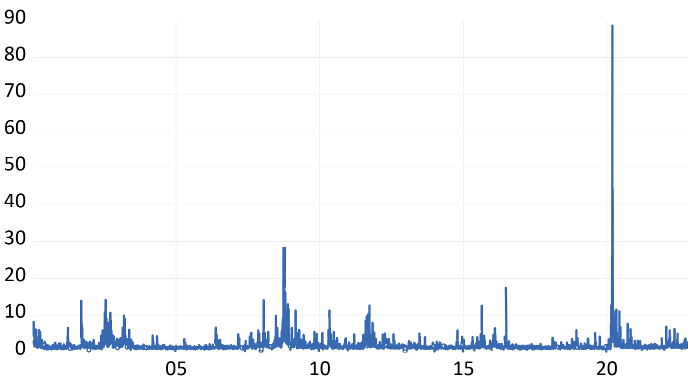


Source: Author, our estimates.

The information impact curve is a useful tool for visualising the response of variance to return surprises. Indeed, negative information on returns affects the variance more than positive information. The GJR-GARCH model allows for an asymmetric response of the variance to positive and negative information. Overall, the model selected is found to have explanatory power for the conditional volatility of market returns.

In addition, the visualization of the conditional volatility of the GJR-GARCH (1,1) model using the GED law is as follows:

Figure 2. *Evolution of the conditional volatility of the GJR-GARCH (1,1) model using the GED law*



Source: Authors, our estimates.

Conclusion

The purpose of this study was to identify overconfidence behaviour in the Belgian investor and to show whether stock price volatility can be explained by this behaviour. Our results show the effective presence of overconfidence through the causal link between lagged market returns and current trading volume. We also show that such sentiment explains the conditional volatility of the Brussels stock market return. Furthermore, the Belgian stock market stands out from the other financial markets on which the same test was performed, by the positive significance of the volume component not related to overconfidence as well.

This last finding raises the question of what other factors we need to consider in understanding the nature and causes of stock market movements. The financial literature reveals that the arguments put forward to understand the volatile nature of financial markets can be grouped into two distinct categories, arguments referring to the teachings of modern financial theory under the assumption of market efficiency, and arguments based on market psychology which behavioural finance considers as "irrationality" arguments referring to behaviour that deviates from the fundamentalist rationality of neoclassical finance.

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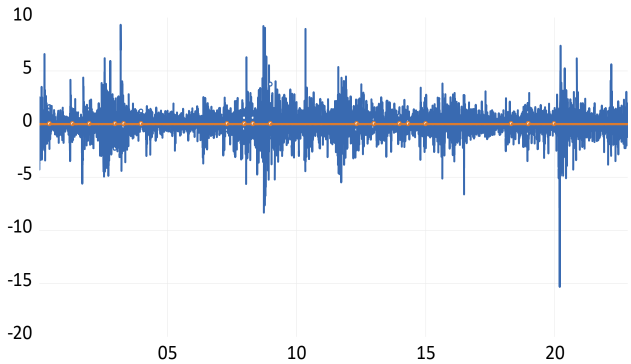
Appendices

Figure A1. *Evolution of the BEL20 index over the period from 03/01/2000 to 21/10/2022*

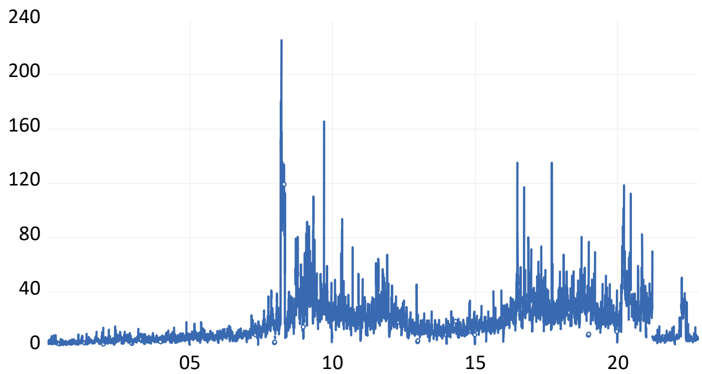
Source: Authors, based on BEL20 index data covering the period from 03/01/2000 to 21/10/2022.

Figure A2. *Evolution of the BEL20 index returns over the period from 03/01/2000 to 21/10/2022*



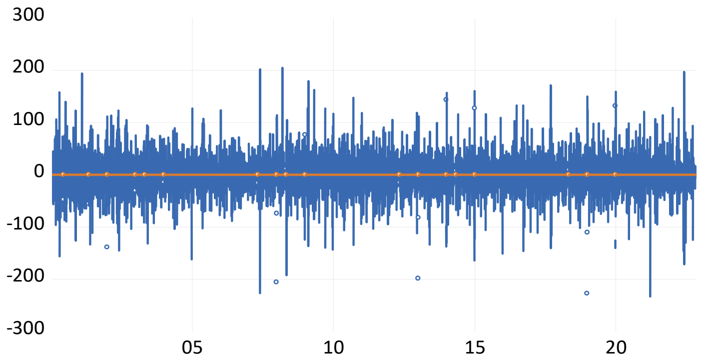
Source: Authors, based on BEL20 index returns data covering the period 03/01/2000 to 21/10/2022.

Figure A3. *Evolution of the volume of transactions over the period from 03/01/2000 to 21/10/2022*



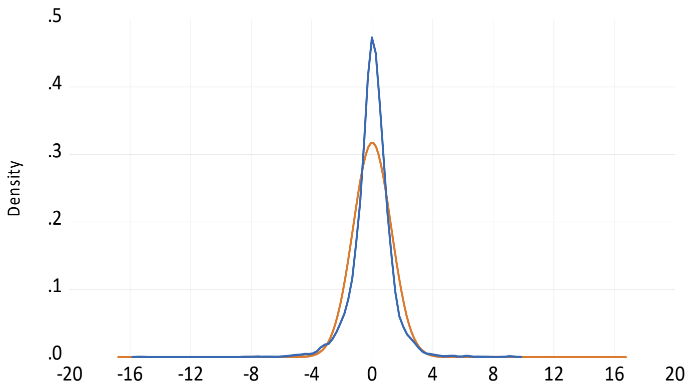
Source: Authors, based on transaction volume data for the period 03/01/2000 to 21/10/2022.

Figure A4. *Evolution of transaction volume returns over the period 03/01/2000 to 21/10/2022*



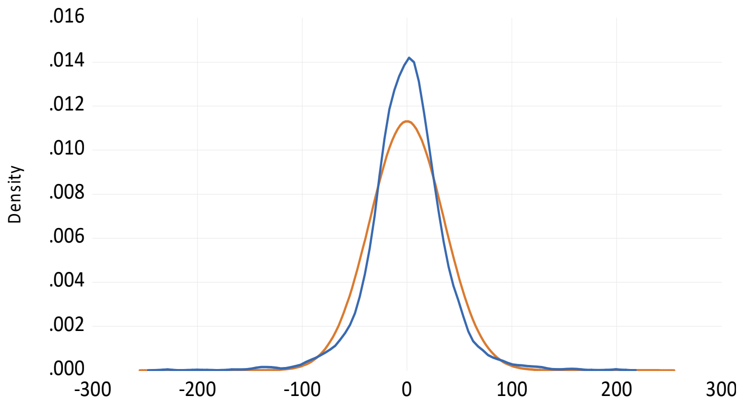
Source: Authors, based on data on trading volume returns over the period 03/01/2000 to 21/10/2022.

Figure A5. *Representation of the density function of the distribution of daily returns of the BEL0 index (in blue) and of a normal distribution (in orange)*



Source: Authors, based on BEL20 index returns data covering the period 03/01/2000 to 21/10/2022.

Figure A6. *Density function representation of the distribution of trading volume returns (blue) and a normal distribution (orange)*



Source: Authors, based on BEL20 index returns data covering the period 03/01/2000 to 21/10/2022.