OVERCONFIDENCE BIAS: EXPLANATION OF MARKET ANOMALIES FRENCH MARKET CASE

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Abstract

In this study, we test whether the overconfidence bias explains several stylized market anomalous, including a short-term continuation (momentum), a long-term reversal in stock returns, high levels of trading volume and excessive volatility. Using data of French stocks market, we find empirical evidence in support of overconfidence hypothesis. First, based on a restricted VAR framework, we show that overconfident investors overreact to private information and underreact to public information. Second, by performing Granger-causality tests of stock returns and trading volume, we find that overconfident investors trade more aggressively in periods subsequent to market gains. Third, based on a two GARCH specifications, we show that self attribution bias, conditioned by right forecasts, increases investors overconfidence and trading volume. Fourth, the analysis of the relation between return volatility and trading volume shows that the excessive trading of overconfident investors makes a contribution to the observed excessive volatility.

Keywords: Overconfidence, Behavioural finance, Over (under) reaction, Trading volume, Volatility

JEL Classification: C52, G12

1. Introduction

Some fascinating events in financial markets, such as a short-term continuation (momentum) and a long term reversal in stock returns, high levels of trading volume and excessive volatility cannot be explained by traditional models based on investors' rationality. A developing strand of the finance literature [Benos, (1998), Daniel *et al.*, (1998), and Odean, (1998)] proposes theoretical models built on the assumption of investor overconfidence to account for these observed anomalies.

Daniel Hirshleifer and Subrahmanyam (1998) develop a behavioural model based on the assumption that investors display overconfidence and self-attribution bias. In their model, the informed traders attribute the performance of ex-post winners to their stock selection skills and that the ex-post losers to bad luck. As result, these investors become overconfident about their ability to pick winners and thereby overestimate the precision of their signals. Based on their increased confidence in their signals, they push up the price of the winners above the fundamental value. The delayed overreaction in this model leads to momentum profits that are eventually reversed as prices revert to their fundamentals (reversals).

According to Gervais and Odean (2001) overconfidence is enhanced in investors that experience high returns, even when those returns are simultaneously enjoyed by the entire market. Odean (1998) and Gervais and Odean (2001) suggest that intertemporal changes in trading volume are the primary testable implication of overconfidence theory.

Moreover, overconfidence is proposed as an important reason for excessive price volatility. Benos (1998) proposes a model in which overconfident traders' aggressive exploitation of their profitable information, together with rational traders' conservative trading strategy, leads prices to move too much in one or the other direction. In their model, Daniel Hirshleifer and Subrahmanyam (1998) show that overconfident investors increases prices volatility at the time reception of private signals.

In this study, we attempt to identify the contribution of overconfidence bias to explaining several stylized market anomalous (momentum, reversals, excessive trading volume and excessive volatility). For this end, four hypotheses derived from overconfidence previous theoretical work are tested: H1, overconfident investors overreact to private information and underreact to public information. H2, market gains (losses) make overconfident investors trade more (less) aggressively in subsequent periods. H3, self-attribution bias, conditioned by right forecasts, increases investors overconfidence and trading volume. H4, the excessive trading of overconfident investors makes a contribution to the observed excessive volatility.

Our contribution is to provide the empirical evidence on various implications of the overconfidence hypothesis by focusing on aggregate French market behaviour.

The methodology followed in this study considers various empirical frameworks. First, a Bivariate Vector Autoregression is employed to study the impulse responses of stock returns to private and public information shocks. Second, Granger causality tests are used for testing the relation between returns and trading volume. Then, two GARCH (EGARCH and GJR-GARCH) models are used to evaluate the effect of investors' error forecasts on their overconfidence. Finally, the conditional variance of GARCH models is estimated by introducing two components of trading volume. The first component, due to past stock returns, is related to investors' overconfidence. The second component is unrelated to investors' overconfidence.

The rest of the paper is organized as follows. In section 2, we present the hypotheses and empirical methodology. Section 3 describes empirical data. Section 4 presents the empirical results. Section 5 concludes the paper.

2. Hypotheses and empirical methodology

2.1. Overconfidence and differential reaction to information

DHS (1998) and Gervais and Odean (2001) models predict that overconfident investors overestimate the precision of their own valuation abilities, in the sense that they overestimate the precision of their private information signals As a result, they make investment decisions by relying on their own private signals while they ignore public signals. Based on these theoretical predictions, we derive the first hypothesis, *H1*, written as follows:

H1. Overconfident investors overreact to private information and underreact to public information.

To identify private and public information, the methodology presented by Chuang and Lee, (2006) is considered. A structural VAR (Vector Autoregression) model is employed. Consider a vector γ_t ($\gamma_t = [V_t, r_t]'$) consisting of two stationary variables: trading volume V_t and stock return r_t series. Based on the Wold theorem, the vector γ_t has a Bivariate Moving Average Representation (BMAR) given by the following relation:

$$\begin{vmatrix} V_t \\ r_t \end{vmatrix} = \begin{vmatrix} B_{11}(L) & B_{12}(L) \\ B_{21}(L) & B_{22}(L) \end{vmatrix} \begin{vmatrix} \varepsilon_t^{private} \\ \varepsilon_t^{public} \end{vmatrix} \quad (1)$$

where $\varepsilon_t^{private}$ and ε_t^{public} are respectively the private and the public information shock. $b_{ij}(L)$ represent the effect of shocks on the trading volume and the stock returns. The shocks on private and public information are distinguished by a restriction imposed on the BMAR. That is, private information shock has a contemporaneous impact on trading volume, while public information shock has no contemporaneous impact on trading volume. This restriction is motivated by several theoretical considerations and it can be formally written as follows:

$$b_{12}(k)/k = 0 = b_{12}(0) = 0 \quad (2)$$

On the one hand, the DHS (1998) overconfidence model shows that excessive trading volume is primarily due to investor's overreaction to their private signals and their underraction to public information. In addition, Campbell *et al.* (1993) show that public information does not affect significantly market trading volume [Chuang and Lee, (2006)].

Really, the BMAR is derived by inverting a Bivariate Vector Autoregression (BVAR), given by the following expression:

$$\gamma_t = \begin{vmatrix} V_t \\ r_t \end{vmatrix} = a(L)\gamma_{t-1} + u_t \equiv \begin{vmatrix} a_{11}(L) & a_{12}(L) \\ a_{21}(L) & a_{22}(L) \end{vmatrix} \begin{vmatrix} V_{t-1} \\ r_{t-1} \end{vmatrix} + \begin{vmatrix} u_{1t} \\ u_{2t} \end{vmatrix} \tag{3}$$

The relation between the BVAR model [Eq. (1)] and the BMAR model [Eq. (3)] is described in the Chuang and Lee (2006) study.

Once a restricted BVAR model of trading volume and stock return is estimated, we can analyze the stock return responses to private and public information shocks to see whether the responses are compatible with the prediction of the overconfidence hypothesis (*H1*).

2.2. Overconfidence and trading volume

Several studies consider the proposition that investor overconfidence generate the high trading volume observed in financial markets [Odean, (1998a, 1998b, 1999), Gervais, and Odean, (2001)]. Gervais, and Odean, (2001) and Odean, (1998) theoretical models predict that high total market returns make some investors overconfident about the precision of their information. Although the returns are market wide, investors mistakenly attribute gains in wealth to their ability to pick stocks. Overconfident investors trade more frequently in subsequent periods because of inappropriately tight error bounds around return forecasts. Alternatively, market losses reduce investor overconfidence and trading, although perhaps not in a symmetric fashion. Thus, the second hypothesis of overconfidence predicts a causality running from stock returns to trading volume.

H2. Market gains (losses) make overconfident investors trade more (less) aggressively in subsequent periods.

To identify the relation between stock returns and trading volume, we use a bivariate Granger causality test. Formally, if the prediction of *Y* using past values of *X* is more accurate than the prediction without using *X* in the mean square error sense ($\sigma^2(Y_t/\Omega_{t-1})$ p $Y_t/\Omega_{t-1} - X_t)$, where Ω_t is the information set at time *t*), then *X* Granger-causes *Y*.

The specification of used test is as follows:

$$V_t = \alpha_{11} + \alpha_{12}|r_t| + \alpha_{13}MAD_t + \sum_{j=1}^{p}\beta_{11j}V_{t-j} + \sum_{j=1}^{p}\beta_{12j}r_{t-j} + \varepsilon_{1t} \tag{4}$$

$$r_t = \alpha_{21} + \alpha_{22}MAD_t + \sum_{j=1}^{p}\beta_{21j}V_{t-j} + \sum_{j=1}^{p}\beta_{22j}r_{t-j} + \varepsilon_{2t}$$

where, r_t is the market return, $|r_t|$ is the absolute value of r_t and MAD_t denotes the mean absolute cross-sectional return deviation:

$$MAD_t = \sum_{i=1}^{N} w_i |r_{it} - r_t| \tag{5}$$

where, r_{it} is the return of stocks *i.*

We choose the number of lag, *p*, by considering the Akaike Information Criterion (*AIC*) and Schwarz criterion.

The first control variable, $|r_t|$, is based on Karpoff's (1987) survey of research on the contemporaneous volume–volatility relationship. The second control variable, MAD_t is motivated by Ross (1989) intuition that in a frictionless market characterized by an absence of arbitrage opportunities, the rate of information flow is revealed by the degree of price volatility.

To test the overconfidence hypothesis, we focus on the null hypothesis that stock returns do not Granger-cause trading volume. The rejection of the null hypothesis (β_{12j} = 0, for any *j*) authenticating our second hypothesis. Moreover, the rejection of the null hypothesis that trading volume does not

Granger-cause stock returns ($\beta_{21j} = 0$, for any *j*) will be an evidence against the market efficiency (trading volume is not a fundamental variable of the firm). The presence of a feedback relation between stock returns and trading volume provides evidence in favor of positive feedback trading.

2.3. Self-attribution and investors' overconfidence

Another central aspect of the overconfidence-related finance literature that we consider is the biased self-attribution; the tendency of the individuals to attribute good outcomes to their own qualities and bad outcomes to bad luck or other factors. The self-attribution bias is considered by some behavioral models that attempt to provide a theoretical framework for the empirical return anomalies documented in the finance literature [DHS, (1998); Gervais and Odean, (2001)]. According to DHS (1998) model, investor overconfidence varies because of biased self-attribution, which means that when investors receive confirming public information, their confidence level increases, but when they receive disconfirming public information; their confidence level falls only modestly.

On the empirical level, biased self-attribution leads investors to become overconfident after a good past performance [Gervais and Odean, (2001)]. Consequently, trading volume is greater positively correlated with past stock returns conditional on investors' right forecasts, than that conditional on their wrong forecasts. Indeed, if investors make a right forecast in that they predict positive stock returns at time *t-1* and realized stock returns are positive at time *t*, then their overconfidence rises significantly and, consequently, they trade more actively in subsequent periods. If, on the other hand, investors make a wrong forecast in that they predict negative stock returns at time *t-1* and realized stock returns are positive at time *t*, then their overconfidence may fall only modestly because they still benefit from market gains [Chuang and Lee, (2006)]. We therefore formally state the third hypothesis as follows:

H3: *Self-attribution bias, conditioned by right forecasts, increases investors' overconfidence and their trading volum*e.

To empirically test this hypothesis, we use two different GARCH-type specifications (EGARCH and GJR-GARCH) taking into account an asymmetric effect in which a negative return shock increases volatility more than does a positive return shock (leverage effect). Equations 6 and 7 represent respectively EGARCH [Nelson, (1991)] and GJR-GARCH [Glosten, *et al.* (1993)] models:

$$\begin{aligned} & r_t = \mu_t + \eta_t \\ & \eta_t / (\eta_{t-1}, \eta_{t-2} \ldots\ldots\ldots, r_{t-1}, r_{t-2} \ldots.) \sim GED(0, h_t), \\ & ln\, h_t = \omega + f_1 \left(\frac{|\eta_{t-1}| + \kappa \eta_{t-1}}{\sqrt{h_{t-1}}} \right) + f_2 h_{t-1} \end{aligned} \tag{6}$$

where μ_t and h_t represent respectively the expected return and conditional volatility.

The asymmetric effect in EGARCH model is represented by the volatility parameter κ. If $\kappa <$ *0,* then conditional volatility tend to increase (to decrease) when the standardized residual is negative (positive).

$$\begin{aligned} & r_t = \mu_t + \eta_t \\ & \eta_t / (\eta_{t-1}, \eta_{t-2} \ldots\ldots\ldots, r_{t-1}, r_{t-2} \ldots.) \sim GED(0, h_t), \\ & h_t = \omega + f_1(\eta_{t-1}^2) + f_2 h_{t-1} + \theta S_{t-1}^{-}(\eta_{t-1}^2) \end{aligned} \tag{7}$$

where $S_{t-1}^{-} = 1$ if $\eta_{t-1} \prec 0$ and $S_{t-1}^{-} = 0$ so not.

The asymmetric effect in the GJR-GARCH model is represented by the volatility parameter θ. If $\theta \succ 0$ then a negative shock has an impact on conditional volatility superior than does a positive shock.

To allow for the possibility of non-normality of the returns distribution, we assume that the conditional errors of EGARCH and GJR-GARCH specifications follow a Generalized Error

Distribution, *GED*. The two different GARCH-type specifications permit decomposing the stocks returns into expected and unexpected returns.

To test whether the self-attribution bias hypothesis can explain the investors' overconfidence dynamic, we estimate the following regression:

$$V_t = \alpha_0 + \alpha_1 \left| r_t \right| + \alpha_2 MAD_t + \alpha_3 r_t + \sum_{j=1}^{p} \beta_j \left(r_{t-j} \times I_{t-j}^{+} \right) + \sum_{j=1}^{p} \gamma_j \left(r_{t-j} \times (1 - I_{t-j}^{+}) \right) + \sum_{j=1}^{p} \lambda_j \left| \eta_{t-j} \right| + \varepsilon_t \tag{8}$$

where η_t is the unexpected return (or forecast error) derived from the GARCH specifications and $\left|\eta_t\right|$ is the absolute value of η_t. The dummy variable I_{t-j}^{+} takes on a value of one if $\mu_{t-1} \times r_t$ f 0 in which μ_t is the expected returns derived from the GARCH specifications, and zero, otherwise.

The β_j and γ_j coefficients are designed to measure the effect of self-attribution bias on trading volume. If investors are subject to self-attribution bias, these coefficients will be positive and that $\sum_{j=1}^{p} \beta_j$ f $\sum_{j=1}^{p} \gamma_j$. The absolute value of forecast error $\left|\eta_t\right|$ is designed to measure the effect of the investors' forecasts precision on their overconfidence. If investors are overconfident, we expect the λ_j coefficients to be negative.

2. 4. Overconfidence and volatility

Overconfidence has been advanced as an explanation for the observed excessive volatility. Odean (1998), Gervais and Odean (2001) show that the volatility is increasing in a trader's number of past success and thereby in a level of investors' overconfidence. Therefore, the fourth hypothesis associated with overconfidence can be written as follows:

H4. The excessive trading of overconfident investors makes a contribution to the observed excessive volatility.

The relation between volatility and trading volume was the subject of many prior researches [Lamoureux and Lastrapes, (1990); Schwert, (1989); Benos, (1998); Albulescu, (2007)]. The objective of testing empirically our fourth hypothesis is to distinguish excessive trading volume of overconfident investors from other factors that affect volatility. In the one stage of the test procedure, the trading volume is decomposed into one component related to investors' overconfidence (*OVER*) and another non-related to the overconfidence (*NONOVER*) and it can be written as:

$$V_t = \alpha + \sum_{j=1}^{p} \beta_j r_{t-j} = \left[\sum_{j=1}^{p} \beta_j r_{t-j} \right] + \left[\alpha + \varepsilon_t \right] = OVER_t + NONOVER_t \tag{9}$$

In the second stage, we include these two components of trading volume into the conditional variance equation of EGARCH and GJR-GARCH models, respectively as follows:

$$\begin{aligned} & r_t = \mu_t + \eta_t \\ & \eta / \left(V_t, \eta_{t-1}, \eta_{t-2}, \ldots.., r_{t-1}, r_{t-2} \right) : \; GED\left(0, h_t\right), \\ & Inh_t = \omega + f_1 \left(\frac{\left|\eta_{t-1}\right| + \kappa \eta_{t-1}}{\sqrt{h_{t-1}}} \right) + f_2 Inh_{t-1} + f_3 NONOVER_t + f_4 OVER_t \end{aligned} \tag{10}$$

and

$$\begin{aligned} & r_t = \mu_t + \eta_t \\ & \eta_t / \left(V_t, \eta_{t-1}, \eta_{t-2} \ldots\ldots\ldots, r_{t-1}, r_{t-2} \ldots. \right) : \; GED(0, h_t), \end{aligned} \tag{11}$$

$$h_t = \omega + f_1(\eta_{t-1}^2) + f_2 h_{t-1} + \theta S_{t-1}^-(\eta_{t-1}^2) + f_3 NONOVER_t + f_4 OVER$$

The parameter f_4 represents the effect of overconfidence on volatility and the parameter f_3 measures the effect of other factors on excessive volatility.

3. Data and descriptive statistics

Our sample consists of 120 French stocks traded in the Paris stocks exchange from January 1995 to December 2004. Data used in this empirical study are price, trading volume and turnover ratio. We use daily data to construct monthly market variables; notably, trading volume (Vol_t), turnover ratio (Tov_t), and return (r_t). Our choice of monthly variables is justified by the fact that the investors' overconfidence level change on the monthly or yearly horizons [Odean, (1998), Gervais and Odean, (2001) and Statman *et al.* (2003)]. Our focus on aggregate investor behavior is motivated in part by the argument of Odean (1998), DHS (2001), Gervais and Odean (2001) that investor behavior should be observable in market level data, and in other part by the idea of Kyle and Wang (1997), Benos (1998), DHS (1998), Hirshleifer and Luo (2001) and Wang (2001) that overconfident investors can survive and dominate the markets in the long run.

The market return is computed as the equally weighted index return:

$$r_t = \frac{1}{N} \sum_{i=1}^{N} r_{it} \tag{12}$$

where r_{it} is the i stock return in t and N represents the number of sample stocks.

The turnover is defined as the ratio of the number of shares traded in a month to the number of shares outstanding at the end of the month. The use of trading volume and turnover is justified by the considerable increases of trades' number. Moreover, one problem with using the number of share traded as a measure of trading volume is that it is unscaled and, therefore, highly correlated with firm size [Chordia and Swaminathan, (2000)].

Figures 1(a) and 1(b) present, respectively, monthly turnover ratio and trading volume, from January 1995 to December 2004. Trading volume gradually increased to reach its maximum during the period of November 1999 until November 2002.

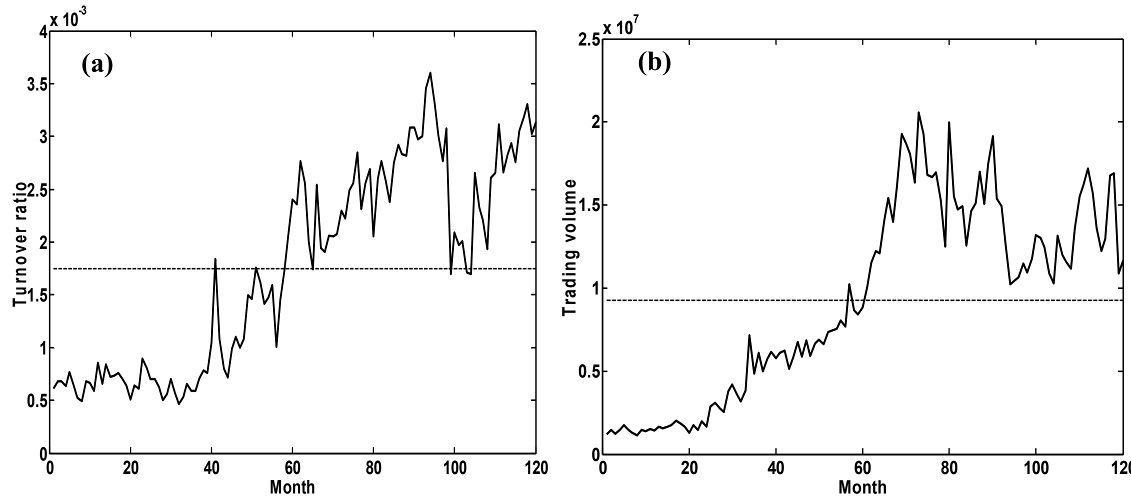

Figure 1. Monthly moving of turnover and trading volume

Source: (own)

Table 1 presents summary statistics on monthly market variables: return, turnover and trading volume. The normality test results show that the three variables distributions are not normal (Skewness ≠ 0 and kurtosis ≠

3). The results of stationary test show that the monthly returns and trading volume series are stationary. About the turnover ratio, Dickey and Fuller statistic (ADF test) is higher than critical value, which means that the series is non-stationary and exhibit a trend. Hodrick-Prescott (1997) algorithm is used to detrending this series.

Table1. Market descriptive statistics

	Return	Turnover	Trading volume
Mean	0.0107	0.0017	9263384
Standard deviation	0.0360	0.0009	5775993
Min	-0.1053	0.0004	1150292
Max	0.0901	0.0036	20563872
kurtosis	3.8096	1.5561	1.7266
Skewness	-0.5889	1.305	0.06813
Jarque and Bera	10.153	10.675	8.2002
ADF test	-8.0367	0.968	-9.98
Critical value (1%)	-4.0407	-3.4885	-3.449

Source: (own)

This table presents market descriptive statistics for monthly return, turnover and trading volume, from January 1995 to December 2004. The table reports, the mean, standard deviation, minimal value, maximum value, Skewness statistic, kurtosis statistic, Jarque and Bera statistic, ADF statistic (Augmented Dickey and Fuller) and critical value of ADF test.

4. Empirical results

4.1. Overconfidence and information differential reaction: Hypothesis 1

In this section, we report the empirical results of the first overconfidence hypothesis. To estimate the BVAR of y_t, we have to choose the number of lags in each equation. Formal overconfidence theories do not specify a time frame for the relationship between returns and trading volume, so we let the data determine the number of monthly lags to include. Specifically, we set five lag ($k = 5$) based on both Schwartz Information Criteria (SIC) and Akaike Criteria (AIC). Two cases are considered to measure V_t series: the turnover, (Tov_t) and the trading volume (Vol_t).

Figures 2 and 3 present the impulse-responses of returns r_t to one standard deviation shocks on public and private information, ε_t^{public} and $\varepsilon_t^{private}$, respectively for Vol_t [Figures 2(a) and 2(b)] and Tov_t [Figures 3(a) and 3(b)]. The shocks on public and private information are orthogonalized using Cholesky decomposition. The dynamic responses of r_t are measured by standard deviations of this variable over 15 months. The figures present a conditional band of the standard error, computed with Monte Carlo simulation method, around the mean response.

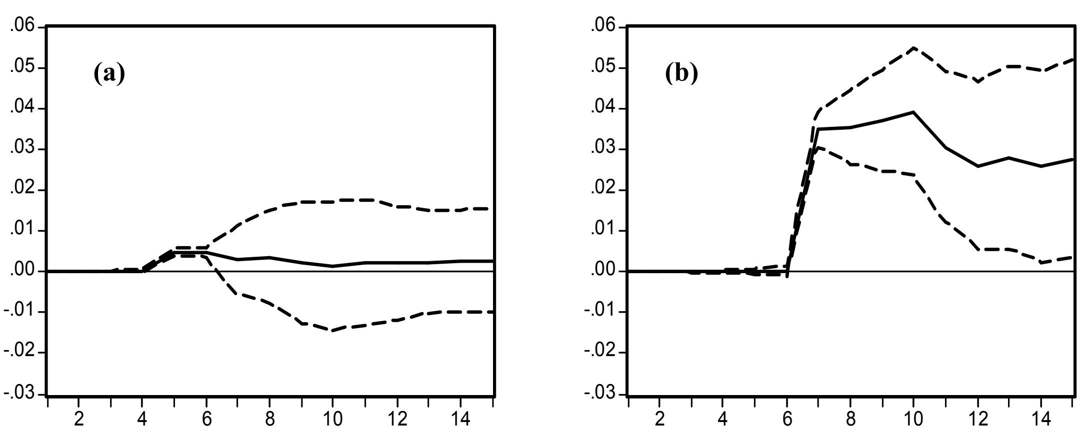

Figure 2. Response of stock returns to private and public information shocks, $V_t = Vol_t$

Source: (own)

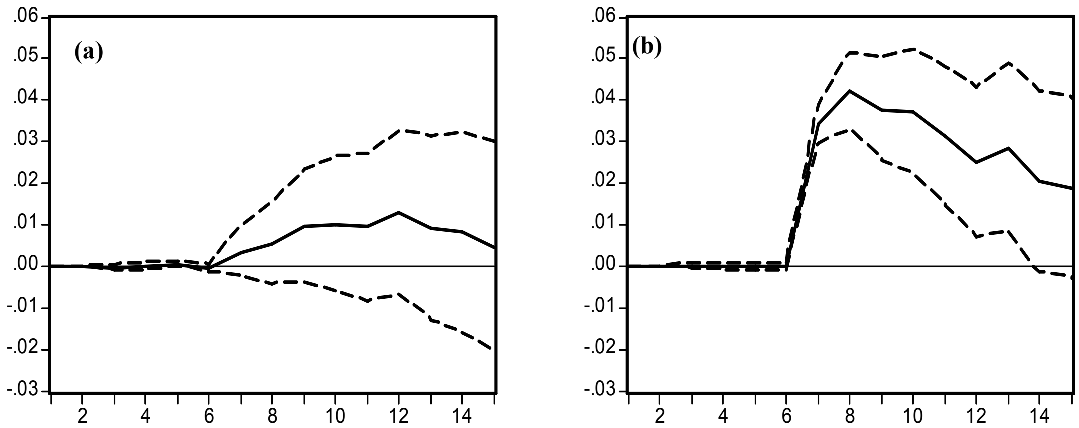

Figure 3. Response of stock returns to private and public information shocks, $V_t = Tov_t$.

Source: (own)

Figures 2(a) and 3(a) illustrate under-reaction of returns to public information shocks. However, an overreaction of returns to private information shocks is showed in Figures 2(b) and 3(b). After an initial under-reaction, stocks prices reach their equilibrium through a correction process. Investors' under- and overreaction to information can work together or independently to generate short-term price continuation returns (*momentum*) and their long-term reversals. Indeed, overconfident investors buy stock which progressed while thinking that market did not sufficiently evaluated it compared to their private information. The returns progress beyond their value suggested by public information. The correction intervenes in long run when public information becomes such as it eclipses the private signals.

4.2. Overconfidence and trading volume: Hypothesis 2

Table 2 summarizes an estimation of Granger causality test in two panels. In Panel A, dependent variables vector is constituted of trading volume and returns $[Vol_t, r_t]'$. In Panel B vector of dependent variables is formed by turnover ratio and returns $[Tov_t, r_t]'$. The estimation results provide confirming evidence that stock returns positively Granger-cause investors' confidence. In addition, the cumulative effect of lagged monthly stock returns on trading volume is positive and significantly different from zero. Moreover, the predictive power in term of $\overline{R}^2$ coefficient is higher for the Tov_t and Vol_t dependent variables compared to that of r_t. This result is consistent with the overconfidence hypothesis suggesting that market gains help to envisage a trading volume increase.

Table 2. Bivariate causality tests of trading volume and stock returns

	Panel A				Panel B			
Dependent Variable	Tov_t		r_t		Vol_t		r_t	
Independent Variable	Tov_{t-j}	r_{t-j}	r_{t-j}	Tov_{t-j}	Vol_{t-j}	r_{t-j}	r_{t-j}	Vol_{t-j}
χ^2_1 (*p-value*)		11.3445 (0.029)		8.7431 (0.0679)		11.254 (0.024)		11.254 (0.0185)
$\sum$*coefficients*	0.8519	0.0003	0.117	-17.953	0.993	3.5893	0.089	-0.005

	Panel A				Panel B			
χ_2^2 *(p-value)*	1.59×10^{-11} (0.000)	10.649 (0.001)	0.275 (0.000)	0.434 (0.509)	1145 (0.000)	5.369 (0.020)	0.1900 (0.664)	2.970 (0.085)
$\overline{R}^2$		0.951		0.145		0.929		0.211
Q(6)		2.017		4.442		2.0167		2.017

Source: (own)

This table presents the results of Granger causality test estimate:

$$V_t = \alpha_{11} + \alpha_{12}|r_t| + \alpha_{13}MAD_t + \sum_{j=1}^{p}\beta_{11j}V_{t-j} + \sum_{j=1}^{p}\beta_{12j}r_{t-j} + \varepsilon_{1t}$$

$$r_t = \alpha_{21} + \alpha_{22}MAD_t + \sum_{j=1}^{p}\beta_{21j}V_{t-j} + \sum_{j=1}^{p}\beta_{22j}r_{t-j} + \varepsilon_{2t}$$

where V_t is the market trading volume (Tov_t or Vol_t) and r_t is the market return, $|r_t|$ is the absolute value of r_t and MAD_t represents the mean absolute cross-sectional return deviation. The χ_1^2 test statistic is used to test the double Granger causality. The χ_2^2 test statistic is used to test the null hypothesis that the sum of the estimated coefficients is equal to zero. The p-value is the probability of obtaining the value of the corresponding test statistic or higher under the null hypothesis. $\overline{R}^2$ is the adjusted coefficient of determination. Q(6) is the Ljung-Box Q-statistic used to test the joint significance of the autocorrelations up to 6 lags for the residuals in each regression.

4.3. Overconfidence and self-attribution bias

Results of the EGARCH and GJR-GARCH models estimation are shown in table 3. An asymmetric relationship between returns and volatility is noted. Indeed, negative return shocks of a given magnitude have larger impact on volatility than positive return shocks of the same magnitude. The GARCH estimator parameter f_2 is significantly positive for EGARCH and GJR-GARCH models. Consequently, the current returns variance is strongly related to that of previous period.

Table 3. Univariate EGARCH and GJR-GARCH regression parameters

Model	**EGARCH**		**GJR-GARCH**	
Parameter	*Coefficient*	*Z- statistic*	*Coefficient*	*Z- statistic*
ω	-1.7286	-1.6763	0.0003	1.8947
f_1	-0.0584	-0.3298	-0.1527	-2.0528
κ (θ GJR -*GARCH*)	-0.2297	-2.1077	0.1893	2.2423
f_2	0.7209	4.4962	0.8597	9.3396

Source: (own)

This table presents the results of the EGARCH and GJR-GARCH conditional variance estimation:

$$r_t = \mu_t + \eta_t$$

$$\eta_t/(\eta_{t-1},\eta_{t-2}.........,r_{t-1},r_{t-2}....):\ GED(0,h_t),$$

$$\ln h_t = \omega + f_1\left(\frac{|\eta_{t-1}| + \kappa\eta_{t-1}}{\sqrt{h_{t-1}}}\right) + f_2 h_{t-1}$$

and

$$r_t = \mu_t + \eta_t$$
$$\eta_t / (\eta_{t-1}, \eta_{t-2}........, r_{t-1}, r_{t-2}....) : \ GED(0, h_t),$$
$$h_t = \omega + f_t(\eta_{t-1}^2) + f_2 h_{t-1} + \theta S_{t-1}^{-}(\eta_{t-1}^2)$$

where, r_t is the market return, μ_t is the expected return and h_t represents conditional volatility.

In order to show the asymmetric response of volatility to good and bad news, we present in figure 4 the estimated news impact curve. This figure displays positive and negative shocks impact on EGARCH conditional variance. It is clear that bad news (negative shock) tends to increase volatility more than good news (positive shock).

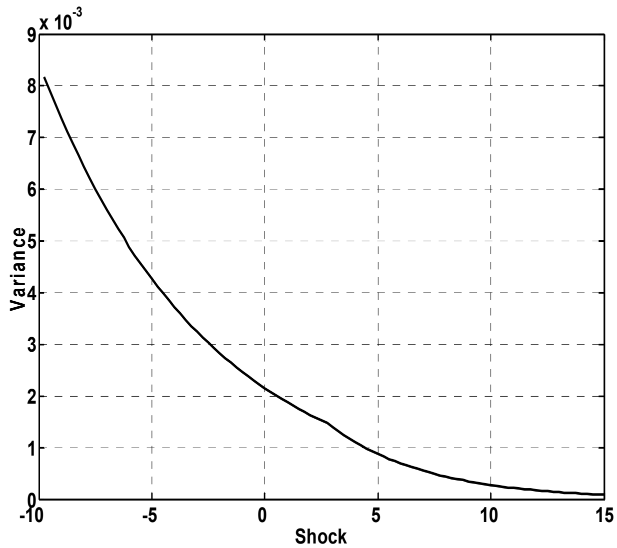

Figure 4. Asymmetric response of volatility to return shocks

Source: (own)

The unexpected return η, derived from GARCH models are then used to study the self-attribution effect on trading volume. Table 4 presents estimation of Eq. (8) in two panels. In panel A, the expected and unexpected returns (η and μ) are derived from the EGARCH model. In panel B, these returns are derived from the GJR-GARCH model. Two types of dependent variables are considered in each panel, turnover, Tov_t and trading volume, Vol_t. The regression is estimated by adopting the lag length of 3. The reason of this choice is due to the fact that our analysis from the bivariate Granger causality tests shows that the most significant positive causal relation between stock returns and trading volume concentrates on the first three months.

The estimation results show that the sum of β_j coefficients which captures the effect of investors' overconfidence on trading volume when they make right forecasts, is positive and the null hypothesis that $\sum_{j=1}^{3} \beta_j = 0$, is rejected. While, the sum of γ_j coefficients that measures the same effect when investors make wrong forecasts is negative and the null hypothesis that $\sum_{j=1}^{3} \beta_j = \sum_{j=1}^{3} \gamma_j$, is rejected. Consequently, the right and the wrong forecasts do not have the same effect on trading volume. The reception of information which confirms investors' forecasts tends to accentuate their overconfidence ($\beta_1 + \beta_2 + \beta_3$>0) while information which contradicts their forecast decreases their confidence ($\gamma_1 + \gamma_2 + \gamma_3$<0). This result suggests that French investors are subject to self-attribution bias. This bias leads them to become more overconfident and trade more aggressively following market gains as they make right forecasts of future stock returns.

Table 4. Relationship between trading volume and stock returns conditional on investor's forecasts

Source of μ and η	Panel A : ARMA (1.1)-EGARCH (1.1)				Panel B : ARMA (1.1)- GJR-GARCH (1.1)			
Dependent Variable	Tov_t		Vol_t		Tov_t		Vol_t	
$\beta_1+\beta_2+\beta_3$	32.776		7.479		40.408		27.036	
$\chi^2_{\beta(1)}$ *(p-value)*	7.562	(0.006)	1.581	(0.208)	11.072	(0.000)	4.720	(0.029)
$\chi^2_{\beta(2)}$ *(p-value)*	8.519	(0.036)	2.16	(0.539)	12.231	(0.006)	5.230	(0.155)
$\gamma_1+\gamma_2+\gamma_3$	-0.414		-8.6		-12.033		-9.4	
$\chi^2_{\gamma(1)}$ *(p-value)*	6.460	0.011)	3.669	(0.055)	7.961	(0.004)	4.626	(0.031)
$\chi^2_{\gamma(2)}$ *(p-value)*	7.248	(0.064)	4.141	(0.246)	9.075	(0.028)	5.4601	(0.141)
$\lambda_1+\lambda_2+\lambda_3$	-0.557		-0.373		-0.596		-0.146	
$\chi^2_{\lambda(1)}$ *(p-value)*	4.503	(0.033)	1.943	(0.163)	5.805	(0.016)	3.169	(0.075)
$\chi^2_{\lambda(2)}$ *(p-value)*	4.509	(0.211)	2.052	(0.561)	5.837	(0.119)	3.234	(0.357)
$\chi^2_{\beta\gamma}$ *(p-value)*	10.91	(0.000)	10.64	(0.000)	15.198	(0.007)	6.987	(0.008)

Source: (own)

This table presents the results of the following regression estimate:

$$V_t=\alpha_0+\alpha_1|r_t|+\alpha_2 MAD_t+\alpha_3 r_t+\sum_{j=1}^{p}\beta_j\left(r_{t-j}\times I^+_{t-j}\right)$$
$$+\sum_{j=1}^{p}\gamma_j\left(r_{t-j}\times(1-I^+_{t-j})\right)+\sum_{j=1}^{p}\lambda_j\left|\eta_{t-j}\right|+\varepsilon_t$$

where V_t is the market trading volume (Tov_t or Vol_t) and r_t is the market return, $|r_t|$ is the absolute value of r_t and MAD_t represents the mean absolute cross-sectional return deviation. $|\eta_t|$ is the absolute value of the unexpected return (or forecast error) at month *t* derived from GARCH (EGARCH and GJR-GARCH) specifications. The dummy variable I^+_{t-j} takes on a value of one if $\mu_{t-1}\times r_t f\ 0$ in which μ_{t-1} denotes the monthly expected return at month *t-1*, and zero otherwise. The $\chi^2_{\beta(1)}$, $\chi^2_{y(1)}$ et $\chi^2_{\lambda(1)}$ test statistics are used to test the null hypothesis that $\beta_1+\beta_2+\beta_3=0$, that $\gamma_1+\gamma_2+\gamma_3=0$ and that $\lambda_1+\lambda_2+\lambda_3=0$, respectively. The test statistics $\chi^2_{\beta(2)}$, $\chi^2_{y(2)}$ and $\chi^2_{\lambda(3)}$ are used to test the null hypothesis that $\beta(j)=0$ for all *j*, $\gamma_{(j)}=0$ for all *j* and $\lambda_{(j)}=0$ for all *j*, respectively. The $\chi^2_{\beta\gamma}$ test statistic is used to test the null hypothesis that $\beta_1+\beta_2+\beta_3=\gamma_1+\gamma_2+\gamma_3$. The *p-value* is the probability of obtaining the value of the corresponding test statistic or higher under the null hypothesis.

4.3. Overconfidence and volatility

Table 5 reports the results from estimating Eq. (10) and Eq. (11). It is seen that the effect of unrelated overconfidence variable on stocks volatility, measured by f_3 parameter, is significantly positive for EGARCH model. Concerning overconfidence effect on volatility, the statically significance of the estimated f_4 parameter, for the EGARCH model, associated with the rejection of null hypothesis that $f_3=f_4$ suggests that overconfidence bias contributes to the return volatility on French securities market.

Table 5. Relationship between conditional volatility and trading volume

	ARMA-EGARCH		ARMA-GJR-GARCH	
ω (t-stat)	-0.0531	(-0.556)	0.0357***	(19.425)
f_1 (t-stat)	-0.3567***	(-11.440)	0.3511***	(17.784)
κ (θ) (t-stat)	-0.1386	(-0.3483)	0.0459	(0.2868)
f_2 (t-stat)	0.8671***	(22.572)	0.8754***	(7.4517)
f_3 (t-stat)	0.0089**	(1.684)	0.0001	(1.380)
f_4 (t-stat)	0.5166***	(3.641)	0.0023	(1.136)
χ^2 (p-value)	13.031	(0.000)	51.576	(0.000)

Source: (own)

This table reports the results of conditional variance equation estimate of the ARMA (1.1)-EGARCH (1.1) and ARMA (1.1)-GJR-GARCH (1.1) models.

$$r_t = \mu_t + \eta_t$$

$$\eta_t / (V_t, \eta_{t-1}, \eta_{t-2}, ..., r_{t-1}, r_{t-2}) : \ GED(0, h_t),$$

$$Inh_t = \omega + f_1\left(\frac{|\eta_{t-1}| + \kappa\eta_{t-1}}{\sqrt{h_{t-1}}}\right) + f_2 Inh_{t-1} + f_3 NONOVER_t + f_4 OVER_t$$

and

$$r_t = \mu_t + \eta_t$$

$$\eta_t / (V_t, \eta_{t-1}, \eta_{t-2} ...., r_{t-1}, r_{t-2} ....) : \ GED(0, h_t),$$

$$h_t = \omega + f_t(\eta^2_{t-1}) + f_2 h_{t-1} + \theta S^-_{t-1}(\eta^2_{t-1}) + f_3 NONOVER_t + f_4 OVER$$

where V_t is the market trading volume (Tov_t or Vol_t) and r_t is the market return. $OVER_t$ is the component of V_t related to lagged market returns at month t, $NONOVER_t$ is the component of V_t unrelated to lagged market returns at month t,

$$V_t = \alpha + \sum_{j=1}^{p} \beta_j r_{t-j} = \left[\sum_{j=1}^{p} \beta_j r_{t-j}\right] + [\alpha + \varepsilon_t] = OVER_t + NONOVER_t$$

The χ^2 test statistic with one degree of freedom is used to test the null hypothesis that $f_3 = f_4$, and the *p-value* is the probability of obtaining the value of the χ^2 test statistic or higher under the null hypothesis.

Note: ***, **, denote significant at the 1%, and 10% levels, respectively.

5. Conclusion

There is a growing literature showing that the overconfidence bias is useful for explaining many asset pricing anomalies. Using French stock market data, this paper provides an evaluation of the overconfidence empirical implications.

The analysis of the returns impulse responses to the private and public information shocks shows that these returns overreact to private information and underreact to public information. Preceded by an initial underreaction, this overreaction is followed by a correction process reaching the stocks prices to the equilibrium. Price behavior in response to private and public information is in favor of our first hypothesis that overconfident investors overreact to private information and underreact to public information.

Granger-causality tests of stock returns and trading volume estimation show that after high returns subsequent trading volume will be higher as investment success increases the degree of overconfidence. This result is consistent with our second overconfidence hypothesis that overconfident investors trade more (less) aggressively in periods subsequent to market gains (losses).

To see whether self-attribution bias causes investors' overconfidence, we investigate the investors' reaction to market gain when they make right and wrong forecasts. Investor's forecasts of future stock returns and forecast errors are derived from two GARCH specifications that allow for asymmetric shocks to volatility. We find that when investors make right forecasts of future returns, they become overconfident and trade more in subsequent time periods. On the other hand, when they make wrong forecasts, their overconfidence may fall modestly. This finding provides empirical evidence in support of our third hypothesis that self-attribution bias, conditioned by right investors' forecasts, increases their overconfidence and their trading volume.

Finally, we study the relation between excessive trading volume of overconfidence investors and excessive prices volatility. The trading volume is decomposed into a first variables related to overconfidence and a second variable unrelated to investors' overconfidence. The analysis of the relation between return volatility and these two variables shows that conditional volatility is positively related to trading volume caused by overconfidence bias. This result is in favor of overconfidence contribution to prices excessive volatility.

Generally, our results provide strong statistical support to the presence of overconfidence bias among investors in French stocks market. This psychological bias constitutes a confirmed explanation of the most stylized market anomalies.

6. References

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