Quantitative Finance and Economics

QFE, 2(2): 348–372.
DOI: 10.3934/QFE.2018.2.348
Received: 25 August 2017
Accepted: 28 February 2018
Published: 31 May 2018

http://www.aimspress.com/journal/QFE

Research article

Volatility analysis of returns and risk: Family versus nonfamily firms

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Abstract: Family firms (FF) tend to be classified as less risky and volatile than nonfamily firms (NFF). This article aims to examine whether there are differences in risk and volatility between FF and NFF, using Portuguese listed firms during 2008 and 2017. Through different models and specifications, we were able to verify that there exists a positive relationship identified in the volatility-return nexus which depends on the model used, and even so, negative in the case of FF, but that volatility is stronger in NFF than in FF as descriptive statistics reveal. Furthermore, it was found no considerable differences in terms of the liquidity-volatility relationship between the two types of firms, and we cannot argue that the negative relationship between returns and turnover is higher in NFF.

It was also found that more illiquid stocks have negative returns but there are no clear differences between FF and NFF. The crisis effect is more able to explain volatility positively than returns negatively, being the impact lower for NFF. Our results do not strictly confirm the fact that FF are less volatile than NFF but provided variables interaction effects we may argue that a risk-averse investor will be more prone to invest in FF stocks, while a risk lover agent will prefer to look at NFF when building their investment portfolios.

Keywords: family firms; non-family firms; risk; volatility; returns; performance; financial crisis
JEL classification numbers: C22, G11, G12, M21

1. Introduction

Family firms represent a large proportion of national economies around the world (Zhou et al., 2017) and dominate global business, generating 70–90% of the world's gross domestic product and 50–80% of job growth in a majority of countries worldwide (Maloni et al., 2017), and account for 40–50% of all jobs of European private employment (European Family Businesses, 2016). We will follow the widely accepted definition of family firms considering it as an organization with direct or indirect decision making control held within a family and at least one family member actively involved in the governance of the organization (European Family Business, 2016; Maloni et al., 2017).

Despite being an interesting case study, family firms are a relatively new maturing field in the literature (Litz et al., 2012; Zhou et al., 2017). This same literature has pointed out some distinguishing characteristics such as being more long-term oriented, fiscally conservative and risk-averse in their business considerations (Cassia et al., 2012). Family firms (FF) may be more focus on reducing the firm risk than nonfamily firms (NFF) since the family sees the firm as a wealth extension and usually intends to pass on the firm to the future generation (Bretton-Miller et al., 2011; Berrone et al., 2012; Erbetta et al., 2013). They may even choose more conservative strategies to avoid risk than NFF, where ownership is more disperse provided that firm's uncertainty can put in place wealth, heritage, reputation, and recognition (Patel and Chrisman, 2013). The same with respect to stakeholders where the literature points that FF seeks business partners with their similar characteristics (Martinez and Aldrich, 2014).

Previous studies over FF focus on the relationship between family control and firm performance (Miralles-Marcello et al., 2014), stock market performance (Miralles-Marcello et al., 2013), innovation performance (Duran et al., 2015; Meroño-Cérdan et al., 2017), corporate social responsibility disclosure (Nekhili et al., 2017), family heterogeneity, control and risk (Lisboa and Miralles-Quirós, 2015), corporate decisions (Lins et al., 2013) and debt policy and firm performance (Vieira, 2017).

Portugal is an interesting case study with respect to risk and volatility behavior of FF as compared to NFF for many reasons. First, provided the fact that FF represents between 75% of the Portuguese firms (European Family Businesses, 2016) and 50% of the Portuguese stock market index (Miralles-Marcello et al., 2013). Second, it possesses a very small market as compared to other countries and thus more exposed to risks (Lisboa and Quirós, 2015). As an example, Portugal suffered from solvency problems since 2008 implying a help request from Troika in order to reduce its economic deficit. Some of the companies went into bankruptcy and thousands faced solvency problems. Despite its relatively small size, Portugal has gained importance in the financial world market and understanding returns volatility and risk is a crucial thematic in this country (Lisboa and Miralles-Quirós, 2015; Miralles-Marcello et al., 2013; Miralles-Marcello et al., 2014; Vieira, 2017). The Portuguese setting is relevant since Portugal belongs to the group of the European countries with the highest proportions of family firms (European Family Business, 2016)[1]. It should be noticed that in Portugal not all FF are small medium enterprises (SMEs) once that we may find among them also large-sized FF.

Understanding volatility dynamics is important for decision making regarding derivative

[1] http://www.europeanfamilybusinesses.eu/family-businesses/facts-figures. Accessed on 1 August 2017.

valuation, hedging and investment. Both public and private sector policymakers, as well as financial market participants, can benefit from knowing how unanticipated news (both good and bad) affects the volatility of prices. Correctly modeling volatility in prices is important for building accurate pricing models, forecasting future price volatility and will further our understanding of the broader financial markets, industries, and the overall economy. Finally, uncertainty about volatility and risk can have important implications for pricing and portfolio decisions (Agarwal et al., 2017). However, it is still not clear at all if FF takes risks more or less (Hiebl, 2012; Huybrechts et al., 2013; Meroño-Cérdan et al., 2017). Some authors results point that FF are more averse to entrepreneurial risk (Short et al., 2009) and that family involvement develops the performance risk-taking relationship if control and socioemotional wealth are considered (Gómez-Mejía et al., 2007). To understand output in family firms, the risk is a key variable (Meroño-Cérdan et al., 2017). Despite being discussed that FF is less risky and volatile than NFF, little empirical evidence exists over the topic and this is the main contribution of the present article. Using volatility models like GARCH initially and then performing OLS regressions, GARCH estimates, Vector Autoregressive analysis and using Granger causality tests for a sample of Portuguese daily price data from 31 December 2007 and 28 April 2017, we try to infer if volatility is stronger in NFF than in FF. As far as we are aware, no previous study has focused on the volatility return relationship comparing FF and NFF using stock market data. We also try to understand the possible explanatory variables able to explain both returns, risk, and volatility in both types of firms accounting for volume traded, market return proxy, turnover, volatility, market capitalization and the number of zero trading days.

The rest of the article develops as follows. In section 2 we present the literature review while reporting hypothesis to be tested, the data used and the methodology settings implemented to infer about the formulated hypothesis. Section 3 presents all the results, the hypothesis validation and further comments taken from the analysis undertaken in comparison terms and for robustness check. Finally, section 4 presents the results discussion while section 5 concludes this work.

2. Hypothesis, data, and method

2.1. Hypothesis setting based on literature review

In economy and finance, volatility is defined as the degree of variation of the price of an asset over time. This is applicable to stocks, exchange rates, commodities or any other asset. Traditional volatility measures include the standard deviation and variance of returns. Moreover, volatility represents a measure of risk since the higher the volatility the riskier the asset is.

Poletti-Hughes and Williams (2017) find that family firms enjoy higher value and tolerate higher levels of risk than non-family firms. However, they use panel data since they joined to their analysis accounting data. To measure the value they use Tobin’s Q and for robustness check the market-to-book value of equity. They follow Gómez-Mejía et al. (2007) in defining their proxy for performance hazard risk (PHR). Negative values of PHR indicate increasing performance as represented by sales, whereas positive values represent performance decreases. Thus, if PHR increases it means firm performance decreased. They also use the market beta, to measure venturing risk[2], and standard deviation of stock returns, to measure total risk, as it represents a composite of different types of risk that a firm takes and defines the general risk preferences of a corporation (Pathan, 2009). Both were used as measures for the additional risk.

In 2017, Lahmiri published several studies on FF stock returns and volatility. Lahmiri (2017a) analyze the existence of fractality and chaos in returns and volatilities of FF listed on the Casablanca Stock Exchange (CSE), as well as in returns and volatility of the CSE market index. In order to quantify fractality in returns, he used detrended fluctuation analysis based on Hurst exponent and fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model, respectively. The author finds evidence that most of FF return listed on CSE exhibit anti-persistent dynamics, while market returns have persistent dynamics. Furthermore, for volatility series, fractality analysis shows that most of FF stocks and market index exhibit long memory in volatility.

Lahmiri (2017b) investigates the existence of multifractality in volatility of Moroccan FF stock returns and in volatility of CSE index returns, using the multifractal detrended fluctuation analysis (MF-DFA) technique, and find evidence of multifractal characteristics in volatility series of both FF stocks and market index. The author also concludes that small variations in volatility of FF stocks are persistent, whilst small variations in volatility of market index are anti-persistent. In addition, Lahmiri (2017c) investigate the multifractality in Moroccan FF stock returns, finding strong evidence of this system. He also documents that short (long) fluctuations in FF returns are less (more) persistent (anti-persistent) than short fluctuations in market indices. One year later, Lahmiri (2018) examines entropy in FF listed on CSE and market index to evaluate randomness in their returns, and find that their respective entropy functions are categorized by opposite dynamics. Information on regular events carried by FF returns is more certain, whereas that carried by market returns are uncertain. The author results are used to recognize the nonlinear dynamics on returns on FF and those of the market.

The goal of this work is to investigate in which type of firms (FF versus NFF) volatility is higher using a sample of Portuguese companies' returns, which, contrarily to aggregate data, allows us to observe the heterogeneity among the different firms.

Stock market returns may be taught as a premium for investors who willingly assume additional risk. In fact, describing and explaining the existent trade-off between asset returns and measured risk (volatility) has been an important task and a still-evolving field of finance and financial econometrics (Lettau and Ludvigson, 2010). Existent studies find that asset returns and volatilities are negatively related. Possible explanations presented were the leverage effect hypothesis, the volatility feedback, and premium effects, and/or behavioral biases (Bekaert and Wu, 2000; Wu, 2001; Bollerslev et al., 2006; Hibbert et al., 2008). Moreover, many of these studies rely on simple econometric models to analyze the return-volatility relationship (basic regression, generalized autoregressive conditional heteroskedasticity (GARCH), and/or vector autoregression (VAR) frameworks.

Thus, return and volatility are negatively related and this relation is more negative the higher the volatility is. If FF has been reported in the literature as being more risk-averse than NFF, then it should be expected that market returns of FF are less volatile than those of NFF. The negative relationship between market volatility and stock returns arise from greater risk premiums and greater

[2] Poletti-Hughes and Williams (2017) argue that venture risk represents firms actions followed when their performance drops below the target, increasing the unexpected outcomes likelihood, causing variance in performance.

illiquidity premiums, all related to higher market risk. Based on this argument we formulate our first (H1) and second hypothesis (H2).

H1: FF faces lower volatility than NFF in the stock exchange market.

H2: On average, the correlation between return and volatility is more negative in NFF than in FF.

Evidence reported in previous literature also suggests that liquidity has a significant role in explaining the cross-sectional variation in stock returns. As suggested by Datar et al. (1998), less liquid, as such more costly to trade, stocks need to provide higher gross returns compared to more liquid assets. The authors use the turnover rate measured by the number of shares traded as a fraction of the number of shares outstanding as a proxy for liquidity. They find that the turnover rate is significantly negatively related to stock returns and that this negative sign on the turnover rate validates the fact that illiquid stocks offer higher average returns than liquid stocks.

Turnover has long been treated as a proxy for liquidity or liquidity risk (Dey, 2005; Callen et al., 2013; Barinov, 2014; Qian et al., 2017). Thus, stocks with higher turnover have a higher level of liquidity. Barinov (2014) suggests that turnover could also proxy for firm-specific uncertainty and higher turnover could explain higher price fluctuations, thus more volatility. Qian et al. (2017) found that turnover has a positive relationship with uncertainty, is negatively related to liquidity measures and positively related to price delay. Provided that FF reveal less uncertainty according to previous authors conclusions we should thus expect the reasoning for our raised hypothesis three (H3).

H3: Turnover has a significant positive relationship with volatility in NFF and null or negative in FF.

Moreover, Fang et al. (2009) provide empirical evidence that liquidity increases firm value (as measured by Tobin's Q). If we use stock returns or market capitalization as proxies for value, liquidity or turnover should increase firm's returns. Provided that managers learn from stock prices and use it to guide corporate investments undertaken (Bakke and Whited, 2010; Brogaard et al., 2017), they would do better investment decisions and will generate higher cash flows, reducing cash flow volatility, increasing returns, which could also lead to lower future expected volatility. If FF are more conservative in investment terms, we should expect that FF are less risky, more stable, have low stock liquidity fluctuations and thus higher returns.

Another possible measure for liquidity is the number of zero stock trades within a given period. As Jiang et al. (2017) suggest, a higher percentage of zero's (when volume traded in a given day equals zero) implies lower liquidity. But if lower liquidity means a higher percentage of zero trades, this means that stock values are lower and thus we should expect lower returns and a negative relationship between the percentage of zeros and stock returns. Illiquid stocks are more likely to experience trading days with zero returns due to either no trading interest or higher trading costs. A higher "zeros values" represents lower liquidity (Lesmond et al., 1999; Jiang et al., 2017). Based on these reasoning's we formulate our fourth, fifth and sixth hypothesis (H4, H5, and H6).

H4: There exists a negative relationship between liquidity/turnover and stock returns independently of the kind of firm analyzed.

H5: The negative relationship between turnover and returns is higher in NFF.

H6: The percentage of zero trades has a negative impact on returns, being higher in FF.

In the following, we will present the data and methodologies used to test each of the previously mentioned hypothesis. Some of the variables and methods were chosen for robustness check and we will provide next all the necessary reasoning for that use.

2.2. Data

We follow Vieira (2017) and use a sample of Portuguese non-financial FF and NFF which have been found to be listed in the Euronext Lisbon exchange market between the period of 2008 and 2017. More precisely, we collected all stock market prices for the firms under analysis from the Bolsapt website, which directly imports price and volume information of the stocks traded in Euronext, with a five-minute delay. Data were collected as available and data periods were made equal among stocks in order to have the same number of observations and an equal sample period for each firm, providing us with a total sample of 2381 observations for each firm for the common period between 31 December 2007 and 28 April 2017.

All complementary accounting data has been extracted from SABI, a private database provided by Bureau van Dijk, complemented with Euronext Lisbon trading data information and with firm's annual reports. The final sample comprises 33 firms, of which 22 were FF (67%), a number which remained unchanged during the entire sample period, clearly indicative of the importance of FF in Portugal. To classify a firm as a FF, we follow Setia-Atmaja (2010) and Vieira (2017) and define it as one in which the founding family or family member controls 20% or more equity being involved in the top management of the firm. Stock returns were computed, as usual, the natural logarithm of the ratio of closing price and the closing price the day before. All other returns were computed following the same methodology.

2.2.1. Dependent variables

In order to understand differences in return and risk/volatility between FF and NFF, we consider as dependent variables volatility and returns, the latter as a proxy for firm value and the primer for firm risk, to test for the six hypothesis explained in the previous subsection. The stock market continues to be a volatile place to invest money, but it is this volatility that also generates the market return investors experience. One way to measure this stock market volatility is through the standard deviation of returns (Poletti-Hughes and Williams, 2017). For stocks, the higher the standard deviation, the greater will be the returns dispersion and higher the investment risk associated. As such, the greater the chance of a lower-than-expected return, the riskier will be the investment. This may explain why some firms are more reluctant to invest in new projects, and the effect should be even stronger in FF, as there is evidence that FF avoids risk more than NFF (Patel and Chrisman, 2013). Therefore, our main goal is to verify if there is a negative relationship between stock returns and volatility, as previously noticed by other authors, but if this relationship differs between FF and NFF.

With respect to the volatility we consider two proxies: 1) we used the GARCH(1,1)[3] model regressing each firm individual return over the stock market return [where the index PSI20 was taken as a proxy like in Teixeira et al., (2016)] with error distribution specified as a generalized error distribution (GED). From here we made the GARCH variance series and applied the square root of the variance series in each day, to compute our volatility (VOLi) variable series, a process repeated for all the 33 firms. 2) Also, the market model was used to estimate volatility and a proxy for systematic risk and venturing risk (in the spirit of Polleti-Hughes and Williams, 2017). From the OLS regressions ($r_i = \alpha + \beta_i . r_m$), the residual series were extracted and the capital asset pricing model

[3] After the usual adjustment tests this model revealed to be the most effective one to represent the 33 individual stock price series.

(CAPM) volatility (volCAPMi) was computed as the 10-day moving window standard deviation. This implied the loss of the first 10 daily observations.

We further include market performance measures, as the financial literature suggest these as better measures of the firm behavior, the market measures, like 1) the firm market return (Ri) as the natural logarithm of the closing price in day t over the closing price in day t-1, provided that higher returns might lead to more volatility and higher risk; 2) market capitalization (RMCi) computed as the natural log of the product between the market closing price in day t and the total number of shares outstanding for that year (data collected from SABI and firms' financial reports from 2008 until 2017). Anderson and Reeb (2003) find that family firms perform better than non-family firms and that family ownership is an effective organizational structure. Meroño-Cérdan et al. (2017) employ a survey in 500 Spanish firms to analyze the effect of firm governance onto the relationship among risk aversion, innovation, and performance, concluding that risk aversion is positively associated with performance only in NFF and that FF are less risky than NFF. Attig et al. (2016) found, through a study of dividend policy, that FF reduces cash holdings and cut investment expenditures even at times of high profitability. Different variables, measures, and methodologies were used for robustness check.

2.2.2. Independent and control variables

Among independent variables, we have considered the stock market return (RM) proxy by the natural logarithm of the ratio between the closing value in day t of the PSI20 index and that of the previous t-1 day. It is well reported in the literature the positive relationship that exists between stock market returns and those of the market index since stocks tend to move along with the market. Another independent variable used was the volume return (RVi) measured as the natural logarithm of the number of shares traded for each stock in day t over the number of shares traded in the previous day. The number of shares traded as well as the number of zero traded within a given day may also proxy for liquidity and will certainly influence returns and volatility as previously mentioned. The number of zeros (NZi) series for each firm were constructed on the basis of a dummy variable where it assumes the value one when the reported volume traded in a given day is zero and zero otherwise.

Previous literature also associated the turnover rate to liquidity and to volatility. We used the turnover rate (TURi) as a measure of liquidity following the fact that Qian et al. (2017) found that turnover has a positive relationship with uncertainty. Stocks with higher turnover have a higher level of liquidity and a lower number of zero trades reported. Barinov (2014) suggests that higher turnover could explain higher price fluctuations, thus more volatility. Provided the evidence, we should expect lower turnover in FF, thus lower volatility and consequently, higher returns in FF. Turnover was computed by the ratio between the number of shares traded in a given day and the number of shares outstanding reported by the firm in that same year.

Finally, we include a crisis dummy (CRISIS) to consider the market recession effect into our analysis which has externally influenced both returns and risk/volatility. Crisis dummy equals one if the fiscal year corresponds to the years of the higher impact of the financial recession (2008 through the end of 2013) and zero otherwise. We should expect a negative impact of the global financial crisis proxy over both returns and risk/volatility.

2.3. Model

Early studies mainly rely on the univariate GARCH model to consider individual asset return volatilities (e.g., Bollerslev, 1986; Bollerslev et al., 1988; Baillie and DeGennaro, 1990; Teixeira et al., 2016). To test our hypothesis and determine whether there are differences in risk and volatility between FF and NFF we start by applying the following OLS regression model:

$$Y_{it} = \alpha_i + \beta_1 RM_t + \beta_2 RV_{it} + \beta_3 TUR_{it} + \beta_4 CRISIS_t + \beta_5 V_{it} + \beta_6 NZ_{it} + \varepsilon_i \tag{1}$$

Where Y_{it} represents one of the two considered independent variables for firm i in year t concerning returns or market capitalization returns (Ri and RMCi); RMi represents the market index return; RVi the return of volume traded for each firm; TURi the turnover ratio for each firm; CRISIS equals one for the days in years 2008 until 2013 and zero otherwise; V_{it} represents the two measures of volatility used, that will be interchanged during estimations (VOLi and volCAPMi); NZi represents the number of zero volume trades treated as a dummy variable which equals one when the volume traded in that day was zero and zero otherwise.

For robustness check, we exclude some variables which are considered as proxies for the same purpose during the estimation process and use different model specifications. With equation (1) we test our hypothesis H1, H2, H4, H5, and H6.

Additionally, and to observe the direct impact of both independent and control variables over risk and volatility, we run the OLS model as defined in equation (1) but using as the dependent variable the volatility.

$$V_{it} = \alpha_i + \beta_1 R_{it} + \beta_2 RM_t + \beta_3 TUR_{it} + \beta_4 CRISIS_t + \varepsilon_i \tag{2}$$

Where V_{it} represents the two measures of volatility used, that will be interchanged during estimations (VOLi and volCAPMi). The rest of the variables have the same interpretation as previously. With equation (2) specification we will try to validate our hypothesis H1, H2, H3, and H5. Additionally, hypothesis H1 and H2 will be verified initially through a simple descriptive statistics performed and which will be presented at the beginning of section 3.

In order to verify if different model specifications change results, we also run a GARCH(1,1) model, defined in this form after specification tests performed. So, we empirically investigate the relationship between returns and volatility with a model built upon GARCH models, with two main contributions. The first is that the developed econometric framework simultaneously accounts for a number of issues that could be important in identifying the true relationship between firms' stocks volatility, risk and other specific market and firm variables and that are usually ignored by existent studies. Second, by using GARCH models we treat heteroskedasticity as a variance to be modeled. As a result, not only are the deficiencies of least squares corrected, but a prediction is computed for the variance of each error term, which is often to be of interest particularly in finance. A GED error distribution was once more considered. The model specification considered was the following:

$$\begin{aligned} &R_{it} = \mu_i + \beta_1 RM_t + \beta_2 TUR_{it} + \beta_3 VOL_{it} + \beta_4 CRISIS_t + \varepsilon_i \\ &\varepsilon_i \sim N(0, h_t) \\ &h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} + \delta_1 RMC_{it} \end{aligned} \tag{3}$$

Where variables have the same interpretation as previously, but besides having returns depending over other market and firm-specific variables we have additionally considered that volatility may also be influenced by returns market capitalization since firm value might also influence volatility as previously mentioned. With this model specification, we hope to validate the hypothesis already tested through OLS for robustness check.

We also move one step further into our analysis and applied vector autoregressive models (VAR), which will be presented next. VAR models are easy to estimate, they have good forecasting capabilities, easy to be applied and we do not need to specify which variables are endogenous or exogenous, since all are endogenous and furthermore, in a VAR system is very easy to test for Granger non-causality, which we will also do (Sims, 1980). Before applying this model some specification tests had to be performed, and we start by testing the unit root hypothesis for each variable. Since all have been previously transformed into returns, the unit root tests indicated series stability. Further, we have started with a VAR model of p^{th} order, denoted VAR(2) and afterward the lag length criteria were applied. In general, for all firms, this test revealed (by the SQ criteria) an optimal number of lags equal to 2.

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \varepsilon_t \tag{4}$$

Where Y corresponds to the vector of variables with Cholesky ordering defined by Ri RM RVi TURi VOLi. After testing for the number of lags we went to verify if variables are cointegrated or not and for each firm the test revealed that there were at least 4 cointegrated variables. Therefore the error correction term had to be included in the VAR. The model becomes a Vector error correction model (VECM) which can be seen as a restricted VAR, using the VECM model specification applied to (4). An important use of VAR is to quantify the effects over time of variables used in the model. With this, we try to answer the question when, for how long, and how much does the shock to one variable impact the other variables. Impulse-response functions describe the response over time of each variable in the VAR to a one-time shock in any given variable while keeping all others constant. Closely associated with the impulse-response function is the forecast error variance decomposition (FEVD). This decomposition refers to the contribution of each innovation to the variance of the forecast error associated with the forecast of each variable in the VAR. For results presentation, we have only considered the forecasting horizon (FH) of 10 days and present the FEVD results of both Ri and VOLi. In the VECM specification, we have considered crisis as an exogenous variable into the model specification.

Using the same VECM specification we finally present the results of Granger causality (GC) tests. It is of interest to know whether one or more variables have predictive content to forecast the variable(s) of interest. With GC we ask whether X is helpful in predicting Y. The corresponding null hypothesis is that all the coefficients on the lags of X are zero. If these coefficients are statistically zero, one says that X does not Granger-cause Y or, equivalently, X does not have any predictive content to forecast Y.

3. Results

In this section, we will try to validate or refute the hypothesis raised previously by applying the models considered in subsection 2.3. We start by presenting the data descriptive statistics and with that answer both hypothesis H1 and H2.

3.1. Data descriptive statistics

Table 1 presents the basic data descriptive statistics in terms of average, standard deviation, minimum, maximum and percentage of zero volume trade identified. Except for turnover, all average values present a negative value which can easily be attributed to the instability of the Portuguese market *faced within this period. The highest standard deviation, as a proxy for risk or volatility, is presented by* NFF, except in volume and turnover, which validates our hypothesis H1 at least at a first sight. However, a lot more instability in standard deviation is observed in volume traded in FF and curiously the highest percentage of zero reported values is always presented by NFF. This is not surprising if we consider that in the set of FF we have some of the highest and more robust firms in terms of market capitalization in Portugal. The lowest returns are always reported in NFF on average. Turnover presents the lowest standard deviation independently of the type of firm considered, being followed by the market expected returns volatility.

Table 1. Data descriptive statistics.

	average	stdv	min	max	%0's
Return FF	−0.0006	9.85%	−1.4573	1.4066	33.38%
Return NFF	−0.0003	17.01%	−1.8886	1.8062	40.17%
RM	−0.0004	1.43%	−0.1038	0.1020	0.00%
Volume FF	−0.0085	103.19%	−5.4467	5.6116	28.40%
Volume NFF	−0.0043	87.51%	−5.1974	4.6618	40.46%
Market Capitalization FF	−0.0006	9.87%	−1.4573	1.4305	33.38%
Market Capitalization NFF	−0.0003	17.02%	−1.8886	1.8062	40.17%
Turnover FF	0.0026	0.63%	0.0000	0.1592	23.00%
Turnover NFF	0.0011	0.25%	0.0000	0.0618	31.95%

In order to observe initially the validation of our hypothesis two (H2) we present the pairwise correlation values and respective significance values (at 5%) in table 2. In table 2 it is also identified the 33 firms considered within our study. For almost all firms in the sample, the correlation between asset returns and the market return reveal to be positive and significant. The same happens between returns and market capitalization returns, were pairwise correlations reveal to be high. This high correlation may cause multicollinearity during estimations and due to that it may sap the statistical power of the analysis, can cause coefficient signs shifts and turner harder a correct model specification. To mitigate the correlation degree we have chosen to work with these variables in different specifications not directly regressing one to the other but as complementary for robustness check.

Curiously, CRISIS is not always negatively correlated with returns as we should initially expect but also most of the time this correlation reveals a non-statistical significance. Volume return when significant is mostly positive and the number of zeros is statistically significant and negatively correlated with stock returns for almost all sample. The turnover when significant is more times positively related with returns while volatility, contrarily to what other previous findings indicate (Bekaert and Wu, 2000; Wu, 2001; Bollerslev et al., 2006; Hibbert et al., 2008). In average terms, as may be seen in the last two lines of table 2, we observe that correlation values are positive for both FF and NFF but clearly values are higher for NFF independently of the volatility measure used.

Table 2. Pairwise correlations and firms identification.

	RM	RV	RMC	TUR	CRISIS	volCAPM	vol	NZ	FF/NFM	Number	Name
R1	0.5531***	−0.0016	0.8835***	0.0455**	−0.0237	−0.0031	−0.0142	0.0004	FF	1	ALTRI SGPS SA
R2	0.3394***	0.0549***	1.0000***	0.0956***	−0.0010	0.0421**	0.0577***	−0.0776***	FF	2	COFINA SGPS
R3	0.0074	−0.0030	1.0000***	0.0120	−0.0008	0.0890***	0.1664***	−0.0830***	FF	3	COMPTA—Equipamentos e Serviços de Informática
R4	0.2323***	0.0339*	0.1710***	0.0414**	−0.0408**	−0.0290	−0.0031	−0.0586***	FF	4	Corticeira Amorim SGPS
R5	0.7182***	−0.0502**	0.3557***	−0.0378*	−0.0112	0.0342*	0.0090	0.0019	NFF	5	EDP—Energias de Portugal SA
R6	0.5942***	0.0614***	1.0000***	0.0115	0.0108	0.0326	0.0272	0.0013	FF	6	MOTA-ENGIL SGPS
R7	0.0104	0.0010	1.0000***	0.0200	−0.0028	0.0444**	0.0884***	−0.0664***	NFF	7	Estoril-Sol
R8	0.0718***	0.0733***	1.0000***	0.0695***	−0.0159	0.0093	0.0142	−0.1278***	NFF	8	FCP—Futebol Clube do Porto
R9	0.6784***	0.0175	1.0000***	0.0399*	−0.0110	−0.0165	−0.0316	0.0005	NFF	9	GALP Energia
R10	0.1600***	0.0467**	1.0000***	0.0614***	−0.0074	0.1160***	0.0810***	−0.0708***	NFF	10	PARAREDE (GLINTT)
R11	0.0063	−0.0099	1.0000***	0.0179	0.0017	0.1005***	0.0595***	−0.0521**	FF	11	Imobiliária Construtora Grão-Pará
R12	0.2336***	0.0126	1.0000***	−0.0202	−0.0332	−0.0054	0.1001***	−0.0596***	FF	12	IBERSOL SGPS
R13	0.3355***	0.0272	1.0000***	0.1351***	−0.0034	0.0338*	0.0357*	−0.0423**	NFF	13	INAPA—Inv. Part. Gestão
R14	0.2570***	0.1190***	1.0000***	0.0254	0.0232	0.0024	−0.0255	−0.0305	FF	14	IMPRESA SGPS
R15	0.5873***	−0.0761***	1.0000***	−0.0997***	0.0100	0.0446**	−0.0127	−0.0023	FF	15	Jerónimo Martins SGPS
R16	0.3436***	0.0565***	1.0000***	0.1584***	−0.0092	−0.0005	−0.0077	−0.0260	FF	16	MARTIFER SGPS SA
R17	0.0376*	−0.0014	1.0000***	0.0117	−0.0015	0.0894***	0.0751***	−0.0382*	NFF	17	Grupo Media Capital
R18	0.3029***	−0.0160	1.0000***	0.1101***	−0.0097	0.1246***	0.0939***	−0.0148	FF	18	NOVABASE SGPS
R19	0.0095	0.0042	0.9998***	0.0343*	0.0032	−0.1450***	−0.3875***	−0.0412**	FF	19	OREY ANTUNES R
R20	−0.0099	0.0027	0.9998***	−0.0021	0.0005	0.0845***	0.0840***	−0.0382*	FF	20	REDITUS
R21	0.5027***	0.0384*	1.0000***	0.0497**	−0.0173	0.0175	−0.0002	0.0017	NFF	21	REN—Redes Energéticas Nacionais
R22	−0.0058	−0.0066	1.0000***	0.0085	−0.0012	0.0824***	0.0067	−0.0058	NFF	22	SCB R
R23	0.0260	0.0705***	0.9800***	0.0832***	−0.0023	0.0002	0.0099	−0.0828***	NFF	23	SPORTING SAD—Sociedade Desportiva de Futebol
R24	0.0071	−0.0030	1.0000***	−0.0016	−0.0038	−0.0005	−0.0253	−0.0200	FF	24	Toyota Caetano—Auto SA
R25	0.5733***	−0.0116	1.0000***	−0.0097	−0.0196	0.0023	−0.0124	−0.0013	FF	25	SEMAPA—Soc. de Investimento e Gestão SGPS

Continued on next page

	RM	RV	RMC	TUR	CRISIS	volCAPM	vol	NZ	FF/NFM	Number	Name
R26	0.0822***	0.1200***	1.0000***	0.0688***	−0.0103	−0.0270	−0.0767***	−0.0157	NFF	26	SLB SAD—Sociedade Desportiva de Futebol
R27	0.4494***	0.0681***	1.0000***	0.1148***	−0.0042	0.0380*	−0.0114	0.0004	FF	27	SONAE.COM SGPS
R28	0.7005***	−0.0154	1.0000***	−0.0608***	−0.0026	0.0005	−0.0342*	0.0145	FF	28	SONAE SGPS
R29	0.3629***	0.0372*	1.0000***	−0.0386*	−0.0335	0.0082	−0.0092	−0.0177	FF	29	SONAE Capital SGPS SA
R30	0.3164***	−0.0386*	1.0000***	0.0244	0.0363*	−0.1946***	−0.2165***	0.0068	FF	30	SONAE Indústria SGPS SA
R31	0.0195	0.0133	0.9957***	0.0928***	−0.0064	0.0564***	0.2009***	−0.1600***	FF	31	Sumolis
R32	0.1741***	0.0389*	1.0000***	0.1448***	−0.0013	0.0478**	0.0629***	−0.1155***	FF	32	SAG GEST—Soluções Automóvel Globais
R33	0.4395***	0.0627***	1.0000***	0.0924***	0.0111	0.0330	0.0317	0.0315	FF	33	Teixeira Duarte—Engenharia e Construções SA
FF	0.2954	0.0177	0.9568	0.0358	−0.0042	0.0149	0.0057	−0.0338	Average	M	PSI 20 market quotes
NFF	0.2379	0.0306	0.9396	0.0464	−0.0077	0.0349	0.0192	−0.0405	Average		

So, at a first sight we cannot validate our raised hypothesis H2 as initially predicted since, on average, the correlation between returns and volatility is more positive in NFF than in FF indicating that returns and volatility move in the same way. However, we may state that the volatility correlation over FF returns is lower which could also validate our hypothesis H1 that FF faces lower volatility than NFF in the stock exchange market.

On average terms, we also verify that the number of zeros reported has a negative correlation with both FF and NFF being lower in the case of FF. Crisis effect has a negative correlation also with both kind of firm returns, but once more we reinforce the idea that this result appear mostly with no statistical significance. On average correlation values between turnover and stock returns, are lower for FF as well as volume returns despite both having a positive correlation. Also, market returns and market capitalization returns reveal a positive correlation on average with stock returns being higher in the case of FF.

3.2. Model results and hypothesis validation

In the following we will present all the results obtained through estimations performed, initially using OLS regressions, next we present the results attained through GARCH, followed by the VECM results in terms of FEVD and the Granger causality results. We start by presenting results regarding equation (1) in table 3.

Results are presented as the number of firms where positive significant, negative significant, non-significant positive and non-significant negative coefficient results were achieved. Afterward, we computed the percentage of significant results for each kind of FF or NFF set considered, presented on the last two horizontal lines of table 3 results.

Table 3. Coefficients significance summary in the model of equation (1).

	Dependent: Asset Individual Return						
	Number of	RM	RVi	TURi	CRISIS	VOLi	NZi
FF	Sig. Pos.	16	6	11	0	2	0
	Sig. Neg.	0	2	4	8	1	10
	Nsig. Pos.	5	11	1	7	10	3
	Nsig. Neg.	1	3	6	7	9	9
NFF	Sig. Pos.	8	5	3	0	0	0
	Sig. Neg.	0	1	0	2	1	5
	Nsig. Pos.	2	5	5	2	9	1
	Nsig. Neg.	1	0	3	7	1	5
FF	% Significant	73%	36%	68%	36%	14%	45%
NFF	% Significant	73%	55%	27%	18%	9%	45%
	Dependent: Return Market Capitalization						
	Number of	RM	RVi	TURi	CRISIS	VOLi	NZi
FF	Sig. Pos.	16	7	11	0	2	0
	Sig. Neg.	0	2	3	7	1	11
	Nsig. Pos.	5	11	1	7	11	2
	Nsig. Neg.	1	2	7	8	8	9
NFF	Sig. Pos.	9	5	2	0	0	0
	Sig. Neg.	0	1	0	2	1	4
	Nsig. Pos.	1	5	6	2	9	1
	Nsig. Neg.	1	0	3	7	1	6
FF	% Significant	73%	41%	64%	32%	14%	50%
NFF	% Significant	82%	55%	18%	18%	9%	36%

Although the sample of NFF represents half the sample of FF we may observe in both a higher percentage of positive significant results regarding market returns meaning that individual stock returns share a common positive sensitivity to true market return shocks. Thus, higher aggregate risk can be revealed by a higher correlation between stocks, which in proportion terms is higher in NFF. This result is kept unchanged independently of the firm performance measure used: Stock returns or market capitalization returns. Volume returns revealed to be in most of the cases no statistical significant, but when significant it has a higher positive relationship with returns and market capitalization in NFF. In regressions, we observe a more significant negative impact over returns of the crisis effect whose sign impact is equal considering the variable number of zeros. Even so, the number of zero volume trades identified reveals to be more significant to explain negative returns than the crisis effect. In percentage terms, our H6 hypothesis can be validated when the dependent variable considered is market capitalization returns, but it does not seem that there are greater differences with respect to the fact that the negative effect of the number of zeros over returns is higher in FF when considering individual stock returns as the dependent.

Turning attention to the turnover variable as a measure of liquidity we observe that in FF the significant positive impact over returns or over market capitalization returns is higher which does not allows us to validate our hypothesis H4 because results reveal that when significant in most of the situations there exists a positive relationship between both variables and independently of the kind of firm. However, in NFF we have more reported situations of non-significant results, meaning that the turnover ratio is more important to be included in FF regression analysis than in NFF. Or, that liquidity is more important to explain stock market movements in FF than in NFF. Moreover, we are not able to validate also our hypothesis 5 once that the negative relationship, when significant, between turnover and returns, is higher in FF and not in NFF as initially predicted.

Turning attention to the volatility variable, computed through the GARCH model, results reveal a weak statistical significance of this variable over returns and market capitalization. Moreover, in most of the firms when non-significant, coefficient results associated to volatility reveal a positive impact over returns. This means that we cannot entirely validate our H1 hypothesis, as already stated previously through descriptive statistics and correlation analysis returns. With respect to H2, we observe through estimations that when negative and significant in both FF and NFF only one firm among the set of each group reveals that volatility has a negative effect on returns. Curiously, this happens in firms from very distinct economic activity sectors (firm 30 in FF and firm 26 in NFF, an industry, and football club company, respectively). So, according to this first set of results, we cannot take many appropriate conclusions with respect to the hypothesis raised.

For robustness check, we have used different specifications of equation (1) and results are presented in table 4. Here the dependent variable considered has always been the stock market individual return but we have used different regressors in order to see if possible multicollinearity problems could explain such different results from those initially expected.

Table 4 reveals, as previously, the same positive effect of market returns over stock individual returns and more positive statistical significance of the turnover rate over stock individual returns especially for NFF. This reinforces the rejection of our H4 and H5 hypothesis provided that results reveal a positive relationship between turnover and returns and no differences in terms of negative effects between FF and NFF. This result is consistent even after taking the volume return and the number of zeros from our regression estimates.

Once more, we cannot clearly state that crisis exerts a significant negative impact over returns revealing that firms which remained quoted in the stock exchanged learned with the financial crisis impact and tried to recover from this negative impact. With respect to our variables of interest, volatility once more seems to have equal significance between FF and NFF, being that in most of the situations results reveal a non-significant impact. Even so, the percentage of firms revealing statistical significance over returns increases when we change the volatility measure from the GARCH to the CAPM volatility, increasing the significance over NFF, even if a more positive impact is revealed in detriment of previous literature findings that volatility and returns have a negative relationship. This means that it clearly depends on the volatility measure considered, as results above confirm. Finally, we should be aware that results remain unchanged even if we take out from the analysis the turnover rate and the crisis effect variable.

Table 4. Coefficients significance summary in model of equation (1): Different specifications.

	Dependent: Asset Individual Return				
	Number of	RM	TURi	CRISIS	VOLi
FF	Sig. Pos.	16	12	1	2
	Sig. Neg.	0	1	7	1
	Nsig. Pos.	5	4	5	10
	Nsig. Neg.	1	5	9	9
NFF	Sig. Pos.	8	8	0	0
	Sig. Neg.	0	0	1	1
	Nsig. Pos.	2	2	2	9
	Nsig. Neg.	1	1	8	1
FF	% Significant	73%	59%	36%	14%
NFF	% Significant	73%	73%	9%	9%
	Dependent: Asset Individual Return				
	Number of	RM	TURi	CRISIS	volCAPMi
FF	Sig. Pos.	16	12	0	2
	Sig. Neg.	0	1	6	1
	Nsig. Pos.	5	4	6	13
	Nsig. Neg.	1	5	10	6
NFF	Sig. Pos.	8	8	0	2
	Sig. Neg.	0	0	3	1
	Nsig. Pos.	2	2	1	7
	Nsig. Neg.	1	1	7	1
FF	% Significant	73%	59%	27%	14%
NFF	% Significant	73%	73%	27%	27%
	Dependent: Asset Individual Return				
	Number of:	RM	RVi	VOLi	NZi
FF	Sig. Pos.	16	9	3	0
	Sig. Neg.	0	0	1	10
	Nsig. Pos.	5	6	8	2
	Nsig. Neg.	1	7	10	10
NFF	Sig. Pos.	8	6	1	0
	Sig. Neg.	0	1	0	5
	Nsig. Pos.	2	3	8	0
	Nsig. Neg.	1	1	2	6
FF	% Significant	73%	41%	18%	45%
NFF	% Significant	73%	64%	9%	45%

Turning now attention to the GARCH model implementation as defined through equation (2), table 5 presents the results obtained by regressing independently and for each firm (results presented in table 5 are read in the same way as in tables 3 and 4), the two volatility measures used, by OLS methods. Results are sensitive to the volatility dependent variable used, especially when we consider NFF since the percentage of significant results change in both panels. Results are consistent with predictions considering the crisis effect since it was initially expected a positive and significant impact of crisis over volatility and which is verified. The impact is reduced when the volatility measure adopted is the CAPM volatility in the case of NFF.

Table 5. Coefficients significance summary in the model of equation (2).

	Dependent: GARCH volatility				
	Number of	Ri	RM	TURi	CRISIS
FF	Sig. Pos.	2	1	14	14
	Sig. Neg.	1	1	2	7
	Nsig. Pos.	10	14	5	1
	Nsig. Neg.	9	6	1	0
NFF	Sig. Pos.	0	4	4	8
	Sig. Neg.	1	2	5	2
	Nsig. Pos.	9	3	2	1
	Nsig. Neg.	1	2	0	0
FF	% Significant	14%	9%	73%	95%
NFF	% Significant	9%	55%	82%	91%
	Dependent: CAPM volatility				
	Number of	Ri	RM	TURi	CRISIS
FF	Sig. Pos.	2	2	13	15
	Sig. Neg.	1	0	4	6
	Nsig. Pos.	13	15	4	1
	Nsig. Neg.	6	5	1	0
NFF	Sig. Pos.	3	1	3	6
	Sig. Neg.	1	0	4	1
	Nsig. Pos.	6	5	3	3
	Nsig. Neg.	1	5	1	1
FF	% Significant	14%	9%	77%	95%
NFF	% Significant	36%	9%	64%	64%

Results also confirm partially our formulated hypothesis H3 since turnover reveals to have a significant positive relationship with volatility but there are no clear differences between FF and NFF. In FF turnover reveals more cases of positive statistical significance, while in NFF we observe more situations where a negative significant coefficient was obtained. Therefore, we cannot confirm the fact that in FF the effect of turnover on volatility is lower, provided these firms characteristics, which impels us to fully validate H3. Moreover, individual stock returns and market returns do not reveal high statistical significance over volatility, independently of the volatility measure used to analyze the effect.

In order to understand if previous empirical findings are sensitive to the type of model used, we move one step forward and present in table 6 the results with respect to the GARCH model results estimated through equation (3) specification presented in the previous section. Results are presented considering two different specifications where in the second-panel volume returns and volatility were removed from the analysis to verify if results remain unchanged.

Table 6. Coefficients significance summary in the model of equation (3).

	Dependent: Asset Individual Return							Dependent: Asset Individual Return				
	Number of	RM	RVi	TURi	VOLi	CRISIS	RMCi*	Number of:	RM	TURi	CRISIS	RMCi*
FF	Sig. Pos.	15	7	10	4	2	5	Sig. Pos.	16	12	1	4
	Sig. Neg.	5	2	3	7	5	6	Sig. Neg.	0	1	9	5
	Nsig. Pos.	1	7	3	7	6	6	Nsig. Pos.	2	5	6	8
	Nsig. Neg.	1	6	6	4	9	5	Nsig. Neg.	4	4	6	5
NFF	Sig. Pos.	5	5	6	4	2	2	Sig. Pos.	6	9	2	3
	Sig. Neg.	3	2	1	2	4	2	Sig. Neg.	2	1	2	2
	Nsig. Pos.	1	2	4	2	2	4	Nsig. Pos.	1	0	2	2
	Nsig. Neg.	2	2	0	3	3	3	Nsig. Neg.	2	1	5	4
FF	% Significant	91%	41%	59%	50%	32%	50%	% Significant	73%	59%	45%	41%
NFF	% Significant	73%	64%	64%	55%	55%	18%	% Significant	73%	91%	36%	45%

Table 6 results show once more that market returns have a positive effect on individual stock returns and that volume returns also show a positive significant impact over returns in most of the situations. Turnover significance remains unchanged independently of the model specification and despite the model used we cannot validate both H4 and H5. However, the significance of turnover over returns in NFF is higher but still positive and not negative as initially expected. The crisis effect is more important to explain returns when we remove both volume returns and volatility from the return regression in the GARCH specification.

However, and provided that the focus of our analysis is between the relationship of volatility and returns, we observe that under the GARCH specification, results seem to indicate that there is more negative statistical significance between the two variables in FF. Thus, considering H4 of a negative relationship between stock returns and volatility, we may state that it differs in terms of firm analyzed (FF versus NFF) being more negative in FF, turning invalid H5. Considering the percentage of significant results obtained for each type of firms, we cannot clearly state that FF face lower volatility than NFF, invalidating H1, and H2 is not also confirmed though GARCH specifications, meaning that on average, the correlation between return and volatility is more negative in FF than in NFF.

We have included into estimations the possible crossed effect between market capitalization and volatility, where in the GARCH specification we included the RMCi variable as an explanatory variable (exogenous in the volatility equation) of volatility movements. We observe through table 6 results that market capitalization is equally important to explain volatility movements in FF, but the significance increases when the model specification excludes volatility and volume from return regressors in NFF.

In order to understand how volatility and returns are able to explain the forecasting error variance of each other, we have run the model specification as provided in equation (4) and results for a 10 days forecasting horizon (FH) are presented in table 7. We are able to observe that on average volatility is more able to explain the forecasting error variance of stock returns in NFF, where return changes are more able to predict volatility in FF. Even so, volatility is more able to explain variance movements in returns than market returns, volume returns and the turnover rate in both FF and NFF. When we look at the FEVD of volatility considering the other variables impact we clearly see that volatility is more affected by stock individual returns, followed by volume returns in FF and turnover movements in NFF. As such, results reveal the explanatory capacity of these variables over both returns and volatility and that results differ depending on the type of firm considered (FF or NFF). The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression, determining how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. Results point that stock return movements are more able to explain volatility than vice versa. In order to lend more support to these findings, we also use equation (4) model specification to compute Granger causality effects. We only present results with respect to stock individual returns and volatility in order to save space.

Table 7. Coefficients FEVD summary in the model of equation (4).

	Var. Decomp. of Ri: 10 days FH						Var. Decomp. of VOLi: 10 days FH					
FF/NFM		Ri	RM	RVi	TURi	VOLi		Ri	RM	RVi	TURi	VOLi
FF	R1	98.75	0.60	0.34	0.19	0.12	VOL1	19.63	4.88	6.46	6.17	62.85
FF	R2	98.06	0.69	0.24	0.12	0.89	VOL2	7.33	6.53	3.78	0.64	81.71
FF	R3	95.78	0.26	0.18	0.54	3.23	VOL3	21.75	0.40	0.17	0.23	77.45
FF	R4	99.34	0.43	0.16	0.06	0.02	VOL4	0.85	0.56	3.96	0.05	94.58
FF	R6	98.41	1.12	0.03	0.15	0.28	VOL6	0.26	1.76	18.34	16.31	63.33
FF	R11	99.31	0.02	0.00	0.03	0.64	VOL11	10.15	0.01	0.01	0.00	89.82
FF	R12	93.27	0.91	0.98	4.62	0.22	VOL12	0.15	3.13	6.77	24.31	65.65
FF	R14	94.95	0.50	0.90	0.13	3.52	VOL14	20.66	1.00	7.87	0.02	70.44
FF	R15	99.31	0.14	0.28	0.23	0.04	VOL15	4.72	0.05	27.46	16.87	50.90
FF	R16	97.67	0.77	0.27	0.56	0.72	VOL16	14.94	3.98	8.81	11.65	60.62
FF	R18	99.01	0.41	0.16	0.28	0.14	VOL18	3.16	0.55	8.22	8.66	79.41
FF	R19	98.61	0.11	0.01	0.03	1.24	VOL19	72.24	0.03	0.07	0.07	27.59
FF	R20	98.50	0.07	0.00	0.03	1.40	VOL20	5.57	0.05	0.06	1.36	92.97
FF	R24	93.32	0.08	0.01	0.00	6.59	VOL24	2.88	0.23	0.00	0.19	96.69
FF	R25	98.31	0.79	0.51	0.07	0.31	VOL25	0.31	2.32	5.65	3.02	88.70
FF	R27	99.02	0.54	0.18	0.08	0.18	VOL27	0.32	3.43	5.65	6.27	84.33
FF	R28	98.99	0.41	0.33	0.22	0.05	VOL28	1.06	4.02	0.77	0.71	93.44
FF	R29	97.78	1.22	0.28	0.45	0.26	VOL29	5.56	0.56	2.20	0.12	91.56
FF	R30	92.88	0.35	0.47	0.30	6.00	VOL30	30.41	2.92	5.76	1.11	59.80
FF	R31	97.99	0.04	0.16	0.29	1.51	VOL31	8.72	0.12	0.57	1.14	89.45
FF	R32	97.91	0.44	0.22	0.23	1.20	VOL32	2.19	0.59	4.01	9.18	84.02
FF	R33	98.54	0.92	0.42	0.08	0.03	VOL33	4.60	0.62	6.78	2.19	85.81
NFF	R5	99.62	0.07	0.03	0.02	0.27	VOL5	0.94	2.36	5.99	0.89	89.82
NFF	R7	95.48	0.22	0.06	0.00	4.23	VOL7	7.79	0.11	0.00	0.12	91.98
NFF	R8	99.79	0.10	0.08	0.02	0.01	VOL8	0.11	1.09	0.07	0.04	98.69
NFF	R9	99.52	0.10	0.31	0.05	0.02	VOL9	0.21	1.29	23.33	12.29	62.87
NFF	R10	88.19	0.46	0.11	0.25	10.98	VOL10	2.93	0.09	0.67	0.27	96.04
NFF	R13	97.70	1.20	0.15	0.56	0.38	VOL13	4.31	0.58	3.04	3.38	88.70
NFF	R17	99.19	0.15	0.01	0.01	0.64	VOL17	13.06	0.05	0.01	0.04	86.84
NFF	R21	98.75	0.65	0.11	0.03	0.46	VOL21	4.32	4.58	2.49	0.28	88.33
NFF	R22	99.03	0.20	0.01	0.01	0.75	VOL22	0.45	0.19	0.01	0.00	99.35
NFF	R23	99.40	0.20	0.08	0.14	0.18	VOL23	0.56	0.01	0.12	3.68	95.64
NFF	R26	97.82	0.52	0.25	1.26	0.15	VOL26	17.50	0.24	5.32	22.86	54.08
FF	Mean	97.53	0.49	0.28	0.40	1.30	Mean	10.79	1.72	5.61	5.01	76.87
NFF	Mean	97.68	0.35	0.11	0.21	1.64	Mean	4.74	0.96	3.73	3.99	86.58

Table 8. Granger causality summary in model of equation (4).

FF/NFM	Return	RM	RVi	TURi	VOLi
FF	R1	→	↔	→	X
FF	R2	→	X	→	←
FF	R3	←	X	→	↔
FF	R4	←	X	X	X
FF	R6	←	X	X	→
FF	R11	X	X	X	↔
FF	R12	←	X	↔	X
FF	R14	←	←	→	↔
FF	R15	X	X	←	X
FF	R16	X	X	←	→
FF	R18	X	X	←	→
FF	R19	X	X	→	↔
FF	R20	X	X	X	↔
FF	R24	X	X	X	↔
FF	R25	←	X	X	↔
FF	R27	←	→	→	X
FF	R28	X	↔	X	X
FF	R29	←	←	↔	X
FF	R30	X	X	←	←
FF	R31	X	X	→	↔
FF	R32	X	→	X	X
FF	R33	←	X	X	X
NFF	R5	X	X	X	←
NFF	R7	X	X	X	↔
NFF	R8	X	X	X	→
NFF	R9	X	←	→	→
NFF	R10	→	X	←	←
NFF	R13	X	→	X	↔
NFF	R17	→	X	X	↔
NFF	R21	↔	X	X	←
NFF	R22	←	X	X	↔
NFF	R23	X	X	X	X
NFF	R26	←	→	↔	→

In accordance with Granger causality, if a variable (X) "Granger-causes" another variable (Y), then past values of X should contain information that helps predict Y above and beyond the information contained in past values of Y alone. Looking at results presented in table 4 we only verify bidirectional causality between stock individual returns and market returns in only one firm which is a NFF. In most of the situations in FF, the causality is unidirectional running from market returns to stock returns. There are very similar results in terms of unidirectional and bidirectional results between stock returns, volume returns and the turnover rate. But, turning attention to our relevant variable volatility and to fulfill our analysis goals, we observe that there are more situations of bidirectional causality between volatility and stock returns. In only 4 firms in NFF and 8 situations in FF. provided the dimension of the each group sample, we cannot confirm that volatility effects are stronger in NFF rather than in FF. Evidence is even more mixed between FF and NFF with respect to unidirectional causality between the two variables: Volatility and stock returns. This evidences and reinforces the findings that we cannot clearly state that volatility differs among FF and NFF, at least in the sample of firms of the Portuguese stock market exchange here analyzed.

4. Discussion

Our main goal was to verify if volatility is stronger in NFF rather than in FF as previously stated by other authors, although not testing directly these differences as we do here. The most interesting finding was to observe that at least for the sample of firms here used, we are not able to confirm previous empirical findings that volatility and returns have a straight negative relationship, independently if we are considering FF or NFF. Volatility bidirectional causalities even seem to be equal in proportionate terms between FF and NFF as Granger causality results reveal, and it was also possible to verify that results seem to point that stocks returns are more able to explain the forecasting error variance predictions of volatility than otherwise, independently also of the type of firm under analysis.

Previous empirical evidence concludes that asset returns and volatility are negatively related, a result attributed to leverage, volatility feedback, premium effects and behavioral biases (Bollerslev et al., 2006; Hibbert et al., 2008). As such, return and volatility are negatively related, being the relationship higher, the higher the volatility is. Under this hypothesis and considering previous literature statements that FF is more risk-averse, we have formulated H1 that FF faces lower volatility than NFF. However, results have revealed different interesting findings. First, in most of the estimation results volatility revealed to have a positive statistical significant impact on stock returns, except when the considered model was the GARCH specification. Thus, results are sensitive to the type of model used, which is expected provided the nature of the underlying data.

Only accounting for descriptive statistics, we are able to confirm H1 considering returns standard deviation as our primary measure of volatility as do Pathan (2009) and Polletti-Hughes and Williams (2017). Moreover, on average, pairwise correlation coefficients indicate a lower correlation between returns and volatility in FF than in NFF, although in average correlation values are positive, thus making us partially accepts our H2 hypothesis. What we could say provided these results are that FF faces lower volatility than NFF reinforcing the validity of H1.

Model results do not allow us to clearly confirm both H1 and H2 since most of the OLS regression results revealed to be no statistically significant between volatility and returns. The situation changes when we turn attention to the GARCH specification results, where we are able to confirm the validity of previous empirical findings of the existence of a negative relationship between volatility and asset returns, but only in the case of FF. In the case of NFF, when significant, results reveal a higher percentage of significant positive results than negative. Thus, at least for the Portuguese stock exchange market, results confirm previous empirical findings of the negative existent relationship between volatility and returns but only in FF. This may be explained by the different number of companies considered within each group, may be due to the specific Portuguese market firm characteristics or even to the type of firms able to be included within the sample of NFF (less robust and of lower dimension than those of the FF group).

We have also hypothesized that turnover has a significant positive relationship with volatility in NFF and null or negative in FF, considering that previous findings (Barinov, 2014; Qian et al., 2017) point that higher turnover leads to more uncertainty and thus to more volatility. If NFF are more volatile than FF, we should thus expect a more significant and positive relationship between turnover and volatility in NFF than in FF. OLS estimations results do not confirm entirely the validity of our hypothesis H3. Results revealed a high positive statistical significance in most of the sample firms in FF and a higher percentage of the negative statistical significant impact of turnover over NFF. As such, if NFF are riskier than FF, there are no considerable differences in terms of liquidity or turnover effects over volatility in these two types of firms.

Considering turnover rate effects over returns, our different models' specification results do not allow us to completely validate hypothesis H4 and H5. This happens since for both FF and NFF it was higher the percentage of situations of positive significance between both variables than a negative one. Results were not even sensitive to the type of model used. However, turnover is not capable of explaining a high percentage of the forecasting error variance of both stock returns and volatility, as the VECM specification allowed us to infer. Granger causality even shows mixed evidence as to the unidirectional causality, running either from turnover to returns or in the other way. Also, if FF are more conservative in investment terms, we should expect these to be less risky, more stable, to have lower stock liquidity fluctuations and thus higher returns. Statistical analysis reveals lower mean return values for FF as compared to NFF. Thus, we have analyzed H5 stating that the negative relationship between turnover and returns is higher in NFF which was also not confirmed, independently of the model specification.

Another possible measure for liquidity is the number of zero trades within a given period (Jiang et al., 2017). Thus, a higher number of zero volume trades reported represents lower liquidity and if FF are less risky, than we should expect the stock market to be more illiquid for FF. Based on this reasoning, we have formulated the last hypothesis (H6) that the percentage of zero trades has a negative impact over returns, being higher in FF. This provided the fact that lower liquidity should be synonymous with lower volatility and consequently lower risk. We found out through estimations that in fact, the number of zeros has a significant negative impact over stock returns independently of the model specification, but it presented no clear significant differences between FF and NFF, thus not allowing us to entirely validate H6.

Finally, we have also considered the financial crisis impact over the analysis and contrarily to previous findings results, stating that crisis has a clear significant impact (Teixeira et al., 2016; Vieira, 2017) on stock market returns, in what respects the volatility-return analysis here performed, the crisis effect consideration depends on the model specification. By considering both OLS and GARCH models, the crisis has no clear relevant effect over returns, but when we turned attention to the volatility as the dependent variable, the crisis revealed to have a highly significant level, which decreases in the case of NFF when the CAPM volatility measure was considered. Thus, the crisis is more able to positively explain positive returns volatility movements, than stock returns negative movements, as also initially expected, since volatility was found to be directly affected by the crisis, among other variables, previously (Polleti-Hughes and Williams, 2017).

From all that has already been analyzed, we may argue that FF seems to have lower volatility than NFF, but investors do not seem to place higher differences among them with respect to investments. Volatility and turnover are positively related in the case of FF and negatively related for NFF as results seem to reveal, but we found no considerable differences in terms of liquidity effects over volatility in these two types of firms. As such, investors do not seem to distinguish their investments by the fact that they are trading FF or NFF stocks. Thus, volatility differences between FF and NFF may arise from other variables rather than investors assessment of the risky nature of firms. This fact deserves a deeper analysis, which will be the focus of currently ongoing research.

5. Conclusions

The goal of the analysis was over volatility and risk differences between family firms and non-family firms. To achieve our goal, we have used volatility models like the GARCH model initially, and afterward performed OLS regressions, GARCH estimates, Vector Autoregressive analysis and we use the Granger causality test. To achieve our goal, we have considered into the analysis a sample of Portuguese daily market price data from 31 December 2007 and 28 April 2017, considering 33 different firms quoted in the Portuguese stock exchange. These firms were classified into FF and NFF and the final possible sample consisted of 22 FF and 11 NFF. From this sample, we try to infer if volatility is stronger in NFF than in FF.

As far as we are aware, no previous study has focused on the volatility return relationship comparing FF and NFF using stock market data. Some conclusions are made regarding the issue, stating that FF are more risk averse and more conservative than NFF. This fact should be reflected in terms of investors' preferences in the market while building their investment portfolios. We also try to understand the possible explanatory variables able to explain both returns, risk, and volatility in both types of firms accounting for volume traded, market return proxy, turnover, volatility, market capitalization and the number of zero trading days.

Results seem to indicate that the relationship between volatility and returns is positive rather than negative, which contradicts previous empirical findings reported. However, it was also proved that results with respect to this relationship are sensitive to the type of model used. Even so, under the GARCH specification, we do find a negative relationship between volatility and returns, but these differ with respect to the type of company since we have obtained more statistical significant regarding this negative effect but for FF. Moreover, the correlation found between volatility and returns was found to be positive but weaker in FF than in NFF. Simple descriptive statistics also reveals that FF are less volatile than NFF. However, further results do not allow us to state this as strict as we should. There are differences among firms, but volatility in the stock market may not be directly related to the type of firm being FF or NFF.

It was also argued that there are no considerable differences in terms of liquidity or turnover effects over volatility in these two types of firms. Moreover, results seem to indicate that turnover has a positive relationship with returns for both firms, thus not allowing to state that the negative relationship between returns and turnover is higher in NFF. More illiquid stocks have negative returns but there are no clearly identified differences between FF and NFF. Finally, crisis explains positively volatility movements, more than it is able to negatively explain returns, but the impact is lower for NFF. This crisis effect may be because NFF are in fact less risk-averse and tend to adopt more aggressive strategies to surpass specific market events. Thus, investors which are more prone to risk should bet in NFF stocks into their portfolio and those which are more risk-averse, should choose assets from FF. This is an interesting topic of research which should be further pursued in order to entirely validate it.

This work suffered from data limitations since in the Portuguese stock market we have few available data and after all the treatments performed the sample had to be even more reduced, where we have ended with the double of FF than the NFF considered in the sample. Thus, in the future, we should be able to include the same number of firms into the analysis to understand better the differences between volatility among FF and NFF. It was at least clear that volatility models more able to describe the specificities of financial data are able to produce results which are more robust and validate previous literature findings regarding the volatility-returns relationship.

Acknowledgments

This work has been in part financially supported by the Research Unit on Governance, Competitiveness and Public Policy—GOVCOPP (project POCI-01-0145-FEDER-008540), funded by FEDER funds through COMPETE2020—Programa Operacional Competitividade e Internacionalização (POCI)—and by national funds through FCT—Fundação para a Ciência e a Tecnologia. Any persistent error or missing's are the authors' entire responsibility.

Conflict of interest

The authors declare that they have no conflict of interest.

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