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Idiosyncratic volatility and earnings quality: evidence from United Kingdom

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**IDIOSYNCRATIC VOLATILITY AND EARNINGS QUALITY: EVIDENCE FROM
UNITED KINGDOM**

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ABSTRACT

Recently, the idiosyncratic volatility has captured much of the attention of the financial literature, being the idiosyncratic volatility puzzle one of the most studied. Our study aims to verify if the financial reporting quality, proxied by earnings quality, an accrual-based measure, has an impact on idiosyncratic return volatility, using as sample the firms listed on London Stock Exchange, and comprising the period between 1988 and 2015. To account for the robustness of our results, we used several control variables, such as leverage, size, ratio book-to-market, firm age and firm performance. We conclude that earnings quality has a positive impact on idiosyncratic volatility, meaning that poorer information quality implies higher idiosyncratic volatility. Posteriorly, we extend our study to a trend analysis, asking if the earnings quality behaviour is related with the idiosyncratic volatility trends. We prove that idiosyncratic volatility does not have a constant upward trend, instead it behaves like ebbs and flows. We found that earnings quality has an impact, albeit small, in the overall trend of idiosyncratic volatility, and also explains its episodic behaviour.

JEL classification: G11, G12, G14, G32, M40

Keywords: Idiosyncratic Volatility, Earnings Quality, Abnormal Accruals, Time Series Analysis

1. INTRODUCTION

For many years, idiosyncratic volatility has been ignored in the literature. The total volatility of a stock is divided into systematic risk and idiosyncratic risk and, according to the Capital Assets Pricing Model (hereafter CAPM), the first risk should be incorporated into the asset pricing and influence the risk premium, since it cannot be eliminated through portfolio diversification. Though, for exogenous reasons, there are investors that prefer to keep undiversified portfolios. So, the idiosyncratic risk should also be incorporated into the assets' price, and reward investors for failing to maintain diversified portfolios (Xu and Malkiel, 2003).

Campbell et al. (2001), after a study of the US stock market between 1962 and 1997, documented that the stock market return volatility had increased over that period. More surprisingly, they show that this rise was mostly due to the individual firm's volatility, since the market and industry volatilities remained relatively constant. This phenomenon created the idiosyncratic volatility puzzle, one of the most studied assets pricing puzzles, with several investigators trying to describe the upward trend in idiosyncratic volatility.

The urge in studying idiosyncratic risk is due to the fact that this component is not zero, and this can lead to several implications. After Campbell et al. (2001) findings, the investors should consider the volatility as a whole and not focus only on market volatility. So, the idiosyncratic volatility matters, affecting the risk-reward relation. Then, it is crucial to understand its behaviour and its determinants to develop better asset pricing models. Plus, attending that is an important component of total volatility, it has consequences on the estimation of options and derivatives value (Dennis and Strickland, 2009). Note that the profits of the option traders depend on the total volatility of the stock return, which includes idiosyncratic volatility, industry-level volatility and market volatility. For arbitrageurs, considering that is main activity is taking advantage of mispriced securities, they are not exposed just to market risk, but also to idiosyncratic risk (Campbell et al., 2001). So, they prefer stocks with less idiosyncratic risk, since it can't be hedge and they are not diversified. In fact, considering that stocks are not rationally priced, idiosyncratic risk discourages arbitrage¹ (Shleifer and Vishny, 1997). More, the theory says that higher idiosyncratic volatility requires more diversification, which means more number of stocks to keep the portfolio variance at a desired level. Thus, the appropriate level of diversification so that the idiosyncratic risk is eliminated depends on the idiosyncratic

¹According to Shleifer and Vishny (1997), stocks with high volatility can be overpriced and this cannot be eliminated with arbitrage because shorting them is risky.

volatility level. However, we should keep in mind that there are investors that hold portfolios composed by many individual stocks and they can face problems as the inability to diversify the portfolio in the recommended way or other exogenous reasons, such as transaction costs or budget restrictions. Hence, they are affected by changes at the firm or industry level, as much as changes at the market level (Campbell et al., 2001). Last, the event studies, like mergers and acquisitions, issues of a new debt or earnings announcements, affect individual stocks. Hence, to calculate the statistical significance of the abnormal returns related to this events, we need to compare the volatility of the individual stocks returns with the industry and the market (Campbell et al., 1997, chapter 4).

Considering all the consequences to financial markets, we have numerous researches that tried to explain the reasons behind the idiosyncratic volatility behaviour. Some of the explanations pointed to this puzzle are the firms becoming riskier (Brown and Kapadia, 2007), the increasing number of new listed firms that starts to issue public equity earlier in their life cycles (Fink et al., 2004), firms' age (Pástor and Veronesi, 2003), firms' size (Bali et al., 2005; Chang and Dong, 2006; Liu and Di Iorio, 2006), leverage increase (Campbell et al., 2001; Fink et al., 2004), institutional ownership (Bennett and Sias, 2003; Malkiel and Xu, 2003; Chang and Dong, 2006), increasing market competition which can affects the firm performance (Irvine and Pontiff, 2009), more volatile fundamentals (Wei and Zhang, 2006), earnings opacity (Hutton et al., 2009), or the deterioration of earnings quality (Rajgopal and Venkatachalam, 2011).

Undeniably, lately, the accounting fundamentals are captivating much of the literature's interest and this pattern is also reflected in the idiosyncratic volatility studies (see Leuz and Verrecchia, 1991 and 2000; Wei and Zhang, 2006; Irvine and Pontiff, 2009; Hutton et al., 2009; Easley and O'Hara, 2004; and Rajgopal and Venkatachalam, 2011). Indeed, we can denote an increase in the number of studies about this matter during the last years, especially after the SEC allegation about the earnings management rise and the number of accounting frauds registered in 2000 (DeFond, 2010). Following that, with this research, we aim to prove whether there is a relationship between idiosyncratic volatility and earnings quality, an accrual-based measure, proxy for information quality, between 1988 and 2015, in the United Kingdom.

There are various ways to measure earnings quality. In fact, defining earnings quality is always a difficult task since no consensual decisions were made. These multiple interpretations about what is earnings quality can be due with the fact that the meaning of 'quality' depends on the decision context (Dechow et al., 2010, and Hermanns, 2006) or that different users use different earnings information to make different decisions (Kirschenheiter and Melumad, 2002).

However, we can say that '*higher quality earnings provide more information about the features of a firm's financial performance that are relevant to a specific decision made by a specific decision-maker*²' (Dechow et al., 2010, p. 1). Actually, investors have different ways to report information related with earnings and the method chosen to report and disclose accounting earnings can have an impact in the information risk, and, consequently, in idiosyncratic risk (Easley and O'Hara, 2004). The best earnings quality proxy to capture the financial reporting quality is abnormal accruals, and taking in consideration the several accruals-based models and its development, we decided to use the Modified Jones (1991) Model to estimate our proxy. This model lies on the idea that accruals are determined by changes in the fundamentals like revenues and property plant and equipment, and such alterations denote earnings management. This measure is an inverse proxy for earnings quality, so higher abnormal accruals implies higher manipulation, which means poorer earnings quality.

To study the relationship between earnings quality and idiosyncratic volatility we will perform two types of analysis. First, we want to prove if there is a cross-sectional relation between earnings quality and idiosyncratic volatility. Yet, our main goal is to show that the time trend in earnings quality explains the time trend in idiosyncratic volatility. So, considering that a cross-sectional relation is not sufficient to prove a time series relationship between the two variables, we will also perform a time series analysis.

Using daily data from the London Stock Exchange, we prove that, there is a positive relationship between earnings quality and idiosyncratic volatility in the cross section. This results are consistent with the theory (Rajgopal and Venkatachalam, 2011) and are obtained after we control for a wide set of possible omitted variables, such as size, age, ratio book-to-market, cash flow volatility, operating performance or leverage. Focusing on the trend analysis, if we consider our sample as a whole, the idiosyncratic volatility performs an upward trend, but not statistically significative. Instead, we can understand that its behaviour is more comparable with ebbs and flows. Our results related with the idiosyncratic volatility trend are in line with the findings of Campbell et al. (2001), who defends an upward trend till 2000, Brandt et al. (2010), and Bekaert et al. (2010), who showed a reversal in the volatility behaviour, proving a downward trend after 2000, and Chen et al. (2012), who displayed that after 2007, idiosyncratic volatility starts to rise again. Relating the earnings quality behaviour with the trends in idiosyncratic volatility, our results show that, if we consider the overall sample, the earnings

² The definition proposed by Dechow et al. (2010) followed the Statement of Financial Accounting Concepts No. 1 (SFAS 1).

quality can explain the idiosyncratic volatility trend. When the sample is separated according with the ups and downs, the earnings quality also explains the episodic reversals.

With this research, we made important contributions. First, to our knowledge, we are the first research that analysis the relationship between idiosyncratic volatility and earnings quality applied to United Kingdom. Second, our sample is extended until 2015, allowing to take conclusions about the recent years. This sample period also lets us know if the findings about the upward trend in idiosyncratic volatility captured by Campbell et al. (2001) and the reversal of its behaviour (Brandt et al., 2010) are also extended to the London market. Third, we do not study a mere cross-sectional relationship, but a time series association between the two variables, so we contribute to the development of the financial literature about the time series trend of idiosyncratic volatility.

These contributions can be important to a set of market intervenients, which decisions can be affected and/ or determined by any of the variables studied in this article. Since we are in an increasingly globalized world, enhanced by a high volume of transactions, including financial ones, we should emphasize the increasing interest of the market players and its regulators in the quality of financial reporting. Analysts, for example, who are seen as “*unbiased and qualified predictors of future earnings*”³, the accuracy of their forecasts is related to the quality of earnings. So their work is influenced by possible earnings management (Dechow et al., 2010). Regarding the firm, itself is a player on the quality of its results. Managers have incentives to manipulate results, as this can be translated into increases in their compensations. Plus, better quality of the financial reports means less information asymmetry between the firms and the investors. Certainly, the regulators pursue reduced information asymmetry since this determinant have a negative impact in the volatility of the stock prices and in the market. So, for them, the information’s about the earnings quality can also be used to make inferences about the market performance. Lastly, we know that the Estate and other public entities perceive the tax collection as their main source of revenue. According to Dechow et al. (2010), the political processes, and the tax and non-tax regulations are affecting and be affected by accounting choices, asserting that the earnings management practices can result in costlier political outcomes and interventions in regulation. The accurate measure of the real firms’ situation can be translated into a correct taxation of their activities. Besides, identify the true performance of the firms of a country can lead to better legislation, more efficient and effective regulatory

³ Dechow et al. (2010), p. 389.

processes, more coherent and fairer tax processes, representatives of the economic reality of a country.

The remainder of this article is organized as follow. Section 2 displays the literature review of the most prominent studies related with idiosyncratic volatility and earnings quality, presenting the hypothesis developed. Section 3 discloses the variables' definition, including the background behind the inclusion of the variables in the study and the methodology used for its measurement. Section 4 reports the data collection procedure and the sample construction criteria. Section 5 presents the methodology along with the analysis of the data and the discuss of the results. Section 6 concludes.

2. LITERATURE REVIEW

2.1. Idiosyncratic Volatility

The Capital Asset Pricing Model, developed by Sharpe, 1964, and Lintner, 1965, signs the beginning of asset pricing theory and says that only the systematic risk of a portfolio should be rewarded through higher return rates. This model, inspired in Markowitz's model about assets diversification, provides a theoretical framework for pricing the risk of the securities, describing the relationship between the expected return and risk ("risk-return trade-off"). The CAPM adds the idea that an individual investment has two types of associated risk: systematic risk and idiosyncratic risk. While the systematic risk is the risk related to market returns and cannot be diversified, the idiosyncratic risk (also known as specific or diversifiable risk.) is defined as the characteristic risk of the firm, i.e., the risk that is specific to each individual stock and that can be reduced through the diversification of the investor's portfolio (that is, by increasing the number of different type of stocks composing the portfolio of financial assets). The idiosyncratic risk is the risk that is uncorrelated with market movements. Since it can be diversified away, it doesn't need to be priced, once unsystematic risk is eliminated if we maintain a well-diversified portfolio⁴ (Lintner, 1965, Sharpe, 1964, and Markowitz, 1959).

Nevertheless, recent literature places into question this assumption and there are many authors who claim that investors actually do not maintain a well-diversified portfolio because of wealth restrictions or personal choice (Liu, 2008, Malkiel and Xu, 2006, and Blume and Friend, 1975).

⁴ According to the 'Modern Portfolio Theory', the investor should invest in different investment instruments to avoid the specific risk. It's not good to invest in just one stock, as if the stock loses value, all portfolio will lose it. This means that the investors can reduce the individual risk of an asset through diversification (Markowitz, 1952).

In fact, 70% of the households contain five or fewer stocks in their portfolios⁵ (Goetzmann and Kumar, 2008) and, in order to diversify the idiosyncratic risk, they should, at least, hold fifty random stocks⁶ (Campbell et al., 2001).

The possibility of idiosyncratic risk being priced in equilibrium had been ignored, but since the investors cannot hold a fully diversified portfolio, the idiosyncratic risk matters and should be priced (Lehman, 1990).

Merton was one of the first authors to question the 'no importance' of idiosyncratic risk. He presented an extent of CAPM theory, suggesting in his work that the specific risk should be priced when investors do not keep their portfolios diversified. The investors do not keep the market portfolio⁷ due to '*various reasons, such as transactions costs, incomplete information, and institutional restrictions including limitations on short sales, taxes, liquidity constraints, imperfect divisibility of securities or any other exogenous factors*' (Malkiel and Xu, 2006, p. 2). Due to this, and since idiosyncratic risk is the largest component of total risk (Campbell et al., 2001), investors need to focus their decisions considering total risk and do not rely just on market risk. This implies that the investor should require a higher return regarding the idiosyncratic risk they face (Merton, 1987). Actually, the lower the level of diversification, the higher the idiosyncratic risk and the risk premium demanded by investors through higher return rates (Xu and Malkiel, 2006, and Merton, 1987). This requirement for higher return rates to compensate the rational investors unable to maintain their portfolio diversified, made the idiosyncratic risk be considered as a pricing factor for the return of risky assets. Indeed, the idiosyncratic risk seems to be the missing factor of the asset pricing models (Malkiel and Xu, 2006, and Goyal and Santa-Clara, 2003).

Once idiosyncratic risk should be priced, it is important to measure it. Yet, computing idiosyncratic risk is not easy, as it is model dependent, i.e., it is not directly observable and depends on the quality of the measure on the accuracy of the model (Malkiel and Xu, 2003). A natural proxy for idiosyncratic risk is idiosyncratic volatility, which represents the standard deviation of a firm's return related to the firm-specific conditions (Chandra and Suardi, 2013).

⁵ For Xu and Malkiel (2006), the great majority of investors do not have the market portfolio. Following a research by Goetzmann and Kumar (2008), only 5% to 10% of the portfolios contain more than 10 stocks and, if we detail this data, we have: over 25% of investors' portfolios contain only one stock, more than 50% contain one to three stocks and more than 70% of the households have five or fewer stocks.

⁶ However, according to Statman (1987), a well-diversified portfolio requires, at least, thirty to forty stocks.

⁷ Market Portfolio is a portfolio formed with all securities presented in the market.

There are two types of methods to estimate the idiosyncratic volatility: direct decomposition methods and indirect decomposition methods. The direct decomposition methods estimate idiosyncratic volatility as the standard deviation of the regression residual of an asset pricing model. As direct decomposition methods, we have CAPM or Fama and French Three-Factor (1993) Model. The CAPM, despite being the most used model in financial literature, has been the target of much criticism. Some critiques are related to the fact that this model does not use other factors besides the market factor to explain the stock's returns (Xu and Malkiel, 2006). Nonetheless, one of the great critiques to this model is that the underlying theory cannot be tested, since it is impossible to estimate the market portfolio (Roll, 1977). Related to the Fama and French Three-Factor Model, despite the extension of the CAPM with the introduction of book-to-market ratio and size effect, it still uses the market portfolio, so it is not an accurate model. On the other hand, it is difficult to estimate all the individual stock's betas and this step is essential to estimate the idiosyncratic volatility (Xu and Malkiel, 2003). However, if we compare these two approaches, the Fama and French Three-Factor model is more precise, since it explains, on average, 93% of the variance on the stock's returns, while CAPM just explain 78% (Fama and French, 1996). As an alternative, the indirect decomposition methods estimate the idiosyncratic volatility as the difference between the individual stock's volatility and market index volatility (Xu and Malkiel, 2003 and 2007). This method provides benefits such as the ease of implementation, computational wise, less calculation requirements and independence of asset pricing model (this means no need to estimate betas). It gives us a simpler way of studying the behaviour of idiosyncratic volatility, demanding less data restrictions. As examples of researches that used the indirect decomposition method, we have Campbell, Lettau, Malkiel and Xu (2001) – they developed the CLMX model, also used by Brandt et al., 2010 -, Goyal and Santa-Clara (2003), and Malkiel and Xu (1997, 2003 and 2006). Yet, using these model can lead to biased results, typically overestimating them. Still, those biases are usually insignificant/ small (Xu and Malkiel, 2003).

Focusing on the studies about idiosyncratic volatility, we can see that the vast majority are more focused on the asset pricing perspective and in the study of the relation between idiosyncratic volatility and return on risk assets. Though, no consensual relation was found. Malkiel and Xu (1997), using the Standard and Poor's 500 stocks indexes during 1963-1994, assert a positive relationship between idiosyncratic volatility and expected stock returns. Goyal and Santa-Clara (2003), using risk measures to estimate the stock market returns, showed results consistent with Malkiel and Xu (1997). Fama and MacBeth (1973), using the NYSE common stocks, find a

positive relation between idiosyncratic volatility and expected returns. On the other hand, Ang et al. (2009) revealed that, when the stock market falls, the increase in idiosyncratic volatility is related with low returns, finding a negative relationship between the two variables. Bali and Cakici (2008), using data from NASQAD, AMEX and NYSE from July, 1958 to December, 2004, studied the cross-sectional relationship between idiosyncratic risk and expected stock returns and proved that there are some characteristics in the definition of our sample, as the data frequency, the breakpoints used to sort stocks, the weighting scheme and the screen used for price, liquidity, and size, that can influence the relationship between idiosyncratic volatility and the expected returns. Yet, no significant relation between the two variables is assured (Bali and Cakici, 2008).

Despite that, during the 90s, great attention was given to the increase of the stock's market volatility. The aggregate market volatility is the *volatility experienced by the holder of aggregate index funds*⁸. It is composed by aggregate market return, industry-level shocks and idiosyncratic firm-level shocks (Campbell et al., 2001). At the time, it was well-known that the market volatility changed over time. However, the attention was misplaced, since no long-run upward trend was verified for the market volatility as a whole (Schwert, 1989, Campbell et al., 2001, and Malkiel and Xu, 2003).

So, in 2001, a study of Campbell, Lettau, Malkiel and Xu, applied to the US stock market from July, 1962 to December, 1997, that used a disaggregated approach, proved that, while the market volatility remains stable, the idiosyncratic volatility increased, being the largest element of firm-specific return volatility (Campbell et al., 2001). This finding becomes one of the most studied asset pricing puzzles, with numerous investigators trying to explain it. Despite fewer in number, we have seen a growth in the research focused on the factors influencing this volatility, trying to explain which of the variables better describe the idiosyncratic risk behaviour.

There are several researches that aims to explain what factors can drive idiosyncratic volatility. Brown and Kapadia (2007) suggested that idiosyncratic volatility is related to the new listing of firms that have more growth and less profit, presenting higher risk, and, consequently, lower survival rate. This kind of firms are also associated with more uncertainty, especially about their average profitability. So, firms return volatility tend to be higher for firms with more volatile profitability, firms that pay no dividends and for young firms, even if this effect of uncertainty declines as firms age (Pástor and Veronesi, 2003). Fink, Grullon, Fink, and Weston

⁸Campbell et al., 2001, p. 1

(2004) showed that firms starting to issue public equity earlier in their life cycles⁹ combined with the increasing number of younger firms can justify the increasing trend in idiosyncratic volatility. The results of Fink et al. (2004) confirmed the ones obtained by Campbell et al. (2001), which also suggested as possible reasons the increasing leverage, the increase in option-based compensation and the higher incidence of spin-offs of conglomerates. Another explanation is given by Bali et al. (2005). They stated that small stocks traded on NASDAQ affect idiosyncratic volatility, proving a negative relationship between firm size and idiosyncratic volatility, partly due to liquidity premiums. This conclusion is also established for the Japanese (Chang and Dong, 2006) and the Australian Stock Market (Liu and Di Iorio, 2012). Irvine and Pontiff (2009) showed that more competitive economies are associated to higher growth in idiosyncratic volatility because in this worldwide environment the firms have fewer market power. The find of these authors can be one reason for the positive relation between idiosyncratic volatility and firm performance pointed by Wei and Zhang (2006). Considering the institutional investors, we can see that in the past they were focused in large stocks, but now they prefer riskier and smaller equities, as they offer better dividends. This change in the investor preferences explains *'why market, in general, and smaller stocks, in particular, have exhibited greater firm-specific risk and liquidity in recent years'* (Bennett, Sias and Starks, 2003, p. 1). So, Malkiel and Xu (2003), when studying the behaviour of idiosyncratic volatility in the US market, confirmed the positive relationship between institutional ownership and idiosyncratic volatility. This relationship sustains to the Japanese Stock Market (Chang and Dong, 2006). The information content on futures earnings is another variable related with idiosyncratic volatility, presenting a negative relationship, since firms with poor prospects of future earnings have the tendency to disclose fewer information. This leads to greater heterogeneity in investors beliefs, which means higher stock return volatility and trading volume (Jiang and Lee, 2006). Another justification was pointed by Kothari (2000) and O'Hara (2003), asserting that the increasing trend in idiosyncratic volatility can be justified by earnings quality. This conclusion was reinforced by Rajgopal et al. (2011), who proved that the time trend in idiosyncratic return volatility is explained by the decrease in financial reporting quality.

⁹ The number of years decrease from forty years in 1960 to less than five in the end of 1990, and, usually, younger firms tend to be riskier and with weaker fundamentals (Fink, Grullon, Fink, and Weston, 2004).

2.2. Idiosyncratic Volatility and Earnings Quality

The information content in earnings changes according to the countries. That alterations are due to the capital market differences, which comprises corporate governance, disclosure practices, financial reporting requirements, and government regulation (Alford et al., 1993).

The quality of the information disclosed is related with the transparency of financial statements. The transparency is defined as a disclosure system that '*reveals the events, transactions, judgements and estimates underlying the financial statements and their implications*' (Pownall and Schipper, 1999, p. 262). Morck et al. (2000), and Jin and Myers (2006) showed that R^2 (proxy for market synchronicity) and the transparency of financial reporting are inversely related, i.e., the lower the R^2 , the higher the idiosyncratic volatility, which denotes more opaqueness (or absence of transparency).

The earnings quality measures aim to capture the transparency of financial reporting data. The poorer the earnings quality, the greater the lack of transparency (Rajgopal and Venkatachalam, 2011).

The method that firms use to report and disclose accounting earnings can have an impact in the information risk¹⁰, and so, in the cost of capital and idiosyncratic risk (Easley and O'Hara, 2004). The accruals' quality is expected to inform investors about the mapping of accounting earnings into cash flows. Since investors value securities by measuring future cash flows, poor accruals quality is expected to weaken this mapping and increase information risk (Francis et al., 2005).

Since investors have different aptitudes to process information related with earnings, and when this is associated with poor earnings quality, we can expect that information asymmetry will increase (Diamond and Verrecchia, 1991). The problem lies in the fact that information asymmetry is costly since investors differently informed intensify the adverse selection risk for the liquidity providers, who demand a larger bid-ask spread, decreasing liquidity and increasing cost of capital (Bhattacharya, Desai and Venkataraman, 2013).

However, disclosures, mandatory or voluntary, can reduce information asymmetries among market participants, which will reduce the costs of capital¹¹ and show which are the most

¹⁰ Information risk is defined as the likelihood of firm-specific information, important for investors decisions, be of poor quality (Francis et al., 2005).

¹¹ Note that information asymmetry affects a firm's cost of capital, suggesting that the cost of capital is determined, in part at least, by corporate decisions unrelated to product market decisions (Easley and O'Hara, 2004).

productive investments (Kothari, 2000). Indeed, managers use voluntary disclosures to reduce information risk and increase stock prices (Graham et al., 2005).

Easley and O'Hara (2004) studied the impact of information in the cost of capital structure, comparing public and private information. They proved that investors ask for higher returns when they hold stocks with higher private information. Greater private information allows to portfolio readjustments, with the investors incorporating stocks with new information and demanding for higher returns. Uninformed investors, however, are not able to readjust the optimal weights and incorporate the new information. This results in two different types of investors who perceives different risks and returns. In the same line of thought, Leuz and Verrecchia (2000) compared also public and private information, but analysed the improvement of the disclosure quality in Germany, when firms moved from German GAAP to IAS or US GAAP. They noticed that firms seeking to raise capital, voluntarily adopt international standards. The remaining firms, especially those with concentrated investor holdings, do not perceive the need to improve the quality of financial disclosure, since they do not experience great information asymmetry. The authors also conclude that the firms that changed for better financial reporting system reduced the information asymmetry component of the cost of capital, as well as the bid-ask spreads, and improved the volume of transactions. This displays us how corporate decisions can affect the firms cost of capital structure, influencing firm's profitability (Easley and O'Hara, 2004).

So, the improvement of public information can mitigate the information asymmetry. This will attract the biggest investors since the securities liquidity rises, which lowers the cost of capital of the firms. This implies that improving the financial disclosure reduces the information asymmetry and the volatility of stock price (Diamond and Verrecchia, 1991), and that poor quality information is related to uncertainty on the future earnings of the firm, leading to increases in idiosyncratic volatility (Pástor and Veronesi, 2003).

Attending to this, I formulate two hypotheses:

H1: Earnings quality is positively related with idiosyncratic volatility.

H2: Lower earnings quality are related with the global tendency in idiosyncratic volatility.

Nevertheless, it is crucial to underlie that recent researches proved that the conclusion of Campbell et al. (2001) is not completely right. When the sample of Campbell is extended, comprising the period between 1925 and 2008, it has been showed that the idiosyncratic volatility decreased dramatically, reversing the time trend seen between 1965-1997. With this

finding, it was concluded that, for the US market, rather than an upward trend, the idiosyncratic volatility behaves like a speculative episode (Brandt et al., 2010). In parallel, Bekaert et al. (2012) did a similar study applied to 23 developed markets, and consistent with Brandt et al. (2010) results, he did not find an upward trend in any of the 23 developed markets. Instead, they describe the behaviour of the idiosyncratic volatility as representing a ‘*stationary autoregressive process that occasionally switches into a higher-variance regime that has relatively short duration*’ (Bekaert et al., 2012, p. 1155), i.e., the idiosyncratic volatility trend exhibits peaks in certain periods. Low-priced stocks held by retail traders and the limited institutional ownership were pointed as reasons for this episode (Brandt et al., 2010). However, Zhang (2010) disagrees with this justification and says that much of the trend and its reversal is explained by the fundamentals, particularly the uncertainty about actual earnings and future earnings growth. Nonetheless, even though the reversal in the volatility trend, all studies previously conducted and that attempt to explain the puzzle of idiosyncratic volatility are not necessarily wrong. However, they must be able to explain not just the upward trend but also the reversals in the volatility (Brandt et al., 2010). Taking this in consideration, I formulate another hypothesis, which not invalidate the last two:

H3: Earnings quality trend is related with the episodic trends in idiosyncratic volatility.

3. VARIABLES MEASUREMENT

3.1. Idiosyncratic Volatility

To estimate the idiosyncratic volatility, we will follow the approach developed by Campbell, Lettau, Malkiel and Xu (hereafter CLMX).

I chose to use this method for three reasons. First, it was developed by four very prestigious authors in the volatility studies (Campbell, Lettau, Malkiel and Xu). Second, this model was published in the most consecrated magazine of the financial area, *The Journal of Finance*. Finally, it is one of the most widely used models when seeking to estimate the idiosyncratic volatility.

First of all, we need to collect return data at the firm level.

After, it is also necessary to group companies according to their SIC classification. According to Fama and French (1997), we have 49 industries¹².

¹² In fact, there are 48 industries. However, firms that do not fit in any of them are grouped in a 49th category.

Then, to obtain the excess daily return¹³, we need to extract the 30-days T-Bill return and divided by the number of trading days in each month.

To begin, it is important to consider that s denote the interval at which the returns are measured. Using returns of interval s , we construct estimates of volatility at intervals t , where t , unless otherwise noted, refers to months.

To estimate the average firm-level volatility ($FIRM_t$) we need to follow four steps:

- i. Estimate the firm-specific residual:

$$R_{ijst} = R_{ist} + \eta_{ijst} \rightarrow \eta_{ijst} = R_{ijst} - R_{ist} \quad (1)$$

Where R_{ijst} is the excess return on day s in the month t of firm j that belongs to industry i , R_{ist} is represented by $\sum_{j \in i} w_{ijst} R_{ijst}$ and is the value-weighted return of industry i on day s in month t , and w_{ijst} is the weight of firm j in industry i on day s in month t .

- ii. Determine the firm specific volatility, that is the sum of the squares of the firm-specific residual of last equation for each firm in the sample:

$$\hat{\sigma}_{\etaijt}^2 = \sum_{set} \eta_{ijst}^2 \quad (2)$$

- iii. Next, we need to calculate the weighted average of the firm-specific volatilities within an industry:

$$\hat{\sigma}_{\eta it}^2 = \sum_{j \in t} w_{ijt} \hat{\sigma}_{\eta j it}^2 \quad (3)$$

Where w_{ijt} is the month- t weight of the firm j that belongs to industry i .

- iv. Finally, we want to ensure that the firm-specific covariance cancel out. So, we average over industries to obtain a measure of average firm-level volatility:

$$FIRM_t = \sum_{i=1}^{49} w_{it} \hat{\sigma}_{\eta it}^2 \quad (4)$$

Where w_{it} is the weight of industry i in the total market in month t .

It is crucial to highlight that for w_{jit} and w_{it} we use the market value related to the period $t-1$.

¹³ Excess Return is measured as an excess return over Treasury Bill rate.

Another important point to mention is that DataStream does not give us the daily stock return but the Return Index (RI), so we need to calculate $\ln \frac{RI_t}{RI_{t-1}}$ to obtain the stock's return.

3.2. Earnings Quality

The best earnings quality proxy to capture the financial reporting quality is abnormal accruals, since '*abnormal accruals are meant to capture distortions induced by the application of the accounting rules or earnings management*' (Dechow et al., 2010, p. 15).

There are several accruals-based models that try to quantify abnormal accruals, and that have seen great development, especially with the goal of improving proxies' accuracy. The most recent researches try to develop the Modified Jones Model. Even this model has undergone some changes and now is more than a simple proxy for earnings management, being able to capture more extensively intentional and unintentional factors that influence the quality of earnings (Dechow, 2010).

Among various discretionary accruals models, Jones Model and Modified Jones Model are the ones which perform the best (Dechow et al., 1995) and are the most accepted by the scientific community, surviving to all the controversy (see Dechow et al., 2010).

The Modified Jones Model lies on the idea that changes in accruals are determined by changes in the fundamentals, as well as in changes in revenues and changes in property, plant and equipment. We estimate total accruals (TA) as:

$$TA_{it} = \delta_0 + \delta_1(\Delta REV_{it} - \Delta AR_{it}) + \delta_2 PPE_{it} + \eta_{it} \quad (5)$$

Where ΔREV is the change in revenues, ΔAR is change in accounts receivable, and PPE is the net value of property, plant and equipment¹⁴.

On the other side, TA_{it} is computed as the difference between TCA (total current accruals) and $DEPN$ (depreciation and amortization expenses). TCA is calculated as:

$$TCA = \Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT \quad (6)$$

Where ΔCA is the change in current assets, ΔCL is the change in current liabilities, $\Delta Cash$ is the change in cash, and $\Delta STDEBT$ is the change in debt in current liabilities.

¹⁴ As Kothari (2005), we used net property, plant and equipment instead of gross property, plant and equipment.

All these variables are scaled by average total assets. The use of the scale aims to reduce heteroscedasticity in residuals (Kothari et al., 2005).

As a result of some researches trying to improve the Modified Jones (1991) Model, Kothari et al. (2005) proved that firm performance affects abnormal accruals. So, to control the effect of performance, he added the variable ROA (return on assets¹⁵) to the model.

Accordingly, our final model to estimate accruals is:

$$TA_{it} = \delta_0 + \delta_1(\Delta REV_{it} - \Delta AR_{it}) + \delta_2 PPE_{it} + \delta_3 ROA_{it} + \eta_{it} \quad (7)$$

This measure is an inverse measure of earnings quality, since abnormal accruals reflects lower earnings quality (Jones, 1991).

Note that $\widehat{\eta}_{it}$ is considered the abnormal accruals, while $\widehat{\eta}_{it}^2$ is the proxy for earnings quality.

3.3. Control Variables

We need to guarantee that we are proving an association between earnings quality and idiosyncratic volatility and not just a relation between two variables that, by coincidence, have merely an upward trend. There are other variables that may influence the relationship between earnings quality and idiosyncratic volatility in the cross-section. So, it is important to understand what other factors, besides the earnings quality, also account for an increase in idiosyncratic volatility. In the Table1, at the end of this section, we have all the details about the control variables, including how they were measured and the expected sign.

3.3.1. Age

According to Pástor and Veronesi (2003), younger firms are associated with the uncertainty about firm's average profitability, which is positively related with firm's idiosyncratic return volatility and its market-to-book ratio. Though, this higher uncertainty of the new listed firms declines over time, since firms are able to learn. So, I believe that idiosyncratic volatility is inversely related with firm's age, since I expect that volatility declines as the firm ages. To estimate the firm's age (AGE), I will use the firm's base date. For UK, DataStream states as base date the one day before trading in the stock starts. I set the firm's age as one in the year

¹⁵ ROA is net income divided by average total assets.

the firm is born and add one in every subsequent year. This procedure follows Pástor and Veronesi (2003).

3.3.2. Book-To-Market

Gaver and Gaver (1993) suggest that larger market-to-book ratio is related with more growth opportunities. Firms with greater growth opportunities experience greater return volatility (Rajgopal and Venkatachalam, 2011). Since, the book-to-market variable is an inverse proxy for firms' growth, it is expected a negative association between this variable and idiosyncratic volatility. The book-to-market ratio (BtM) is measured as the ratio of book value of equity (measured as the difference between total assets and total liabilities) and market value equity.

3.3.3. Cash Flow Volatility

The firm-level stock return depends on the expected return news and unexpected cash flow news (Vuolteenaho, 2002). This means that the conditional cash flows variance has an impact in idiosyncratic volatility and so it will be proxied by the cash flows variance. It is expected a positive impact. This variable, VCFO, is measured for each firm-year as the variance of annual operating cash flow scaled by total assets over the trailing five-year window for that firm.

3.3.4. Disclosure of value-relevant information

The analysis of the disclosures released as part of earnings announcements proved a positive relationship between the temporal increase in return volatilities around earnings announcements and its concurrent disclosures (Francis, Schipper, and Vincent, 2002). Then, it is predictable that extended disclosures are related to a temporal increase in idiosyncratic volatility. To measure this, it will use the squared annual buy-and-hold return (RET^2), a proxy that probably contains value relevant information that is disseminated during the fiscal year. It is squared since idiosyncratic volatility does not depend on the sign.

3.3.5. Earnings Informativeness

While ones defend that an increase in earnings management is positively related with idiosyncratic volatility, since reduces the accuracy of the earnings signal (Rajgopal and

Venkatachalam, 2011), others assure that when earnings management is detectable by the investors it can be interpreted as a positive supplementary information to them (Watts and Zimmerman, 1990). Subramanyam (1996) showed that discretionary accruals have positive consequences, saying that management discretion can improve the earnings informativeness. Then, we expect that the association between lower earnings quality and an increase in idiosyncratic volatility can be due to earnings informativeness. To estimate this, we will use next year's operating cash flows (CFO_{t+1}). The operating cash flows are measure as the difference between net income and total accruals, scaled by average total assets.

3.3.6. Leverage

Firms in a leverage situation, probably experience financial distress (Cao et al., 2007). According to Ang et al. (2009), as leverage rises, the power of the negative relationship between idiosyncratic volatility and stock returns increases. An increase in leverage could imply an increase in return volatility (Black, 1986). So, we will expect a positive association between the two variables. Leverage (LEV) is determined as the ratio of long term debt divided by the book value of total assets.

3.3.7. Operating Performance

According to Hanlon (2005), there is a negative relation between operating performance and stock returns volatility. Following the approach used by Wei and Zhang (2006), to estimate the firm's operating performance, I will use the return on equity (ROE) measured as the ratio between net income and book value of equity. Further, following Rajgopal and Venkatachalam (2011), I will use the lagged ROE.

3.3.8. Size

Several studies shown that small firms are related with higher idiosyncratic volatility. This negative relation between the two variables was stated across numerous stock markets, including United States (Pástor and Veronesi, 2003, and Bali et al., 2005), Japan (Chang and Dong, 2006) or Australia (Liu and Di Iorio, 2012). Agreeing with Brandão, Cerqueira and Lopes (2012), we will measure the firm's size (SIZE) as the natural logarithm of total assets.

3.3.9. Sophistication of Investors

The rise in idiosyncratic volatility can be explained by the increasing number of ‘noise traders’ in the markets, i.e., more uniformed investors trading stocks. For Harris (2003), this increase in ‘noise traders’ is related with the beginning of on-line trading. On the other side, Brandt et al. (2010) showed that the episodic idiosyncratic volatility phenomenon is stronger among low-priced stocks and this kind of stocks are held by retail investors rather than institutional investors. So, we expect that a positive relationship between the quantity of ‘noise traders’ and idiosyncratic volatility. As proxy for investor’s sophistication, we will use the number of analysts following a company. To estimate that, we will use the number of analysts who provide earnings per share estimate (NANAL).

3.3.10. Stock Return Performance

After the stocks price’s decreases, the stock return volatility increases. the phenomenon stated before was documented at the aggregated level, and can be due with a strong negative contemporaneous association between stock return performance and idiosyncratic volatility (Duffee, 1995). According to that, I will compute the stock return performance (RET) as the contemporaneous annual buy-and-hold return.

Table 1: Variables Description

Description of all control variables, that we believe that affect idiosyncratic volatility despite earnings quality. Includes also the abbreviation used in the methodology and the expected sign of our predictions.

| Variable | Abbreviation | Definition | Expected Sign |
|----------------------------|------------------|---|---------------|
| Firm Age | AGE | Set to 1 in the year the firm is born and add 1 in the subsequent years | - |
| Book-to-Market | BtM | Ratio between the Book Value of Equity and the Market Value of Equity | - |
| Cash Flow Volatility | VCFO | Standard Deviation of Operating Cash Flows in a 5-year window | + |
| Value Relevant Information | RET ² | Annual Buy and Hold Return | + |
| Earnings Informativeness | CFO | Net Income minus Total Accruals, divided by Average Total Assets | - |
| Leverage | LEV | Ratio between Long Term Debt and Total Assets | + |
| Operating Performance | ROE | Net Income divided by Total Shareholders’ Equity | - |
| Size | SIZE | Natural Logarithm of Total Assets | - |
| Investor’s Sophistication | NANAL | Number of Analysts Following (ESP1NE on DataStream) | + |
| Stock Performance | Return RET | Contemporaneous Buy and Hold return | - |

4. DATA AND DESCRIPTIVE STATISTICS

4.1.Data

To build the sample and study the United Kingdom stock market, I will use the London Stock Exchange (LSE) data, collected from Thomson Financial DataStream, and comprehending a period between January, 1988, and December, 2015. Taking into account the parameters estimation, especially for the variables that required lag values and residuals standard deviations, I collected data between January, 1982, and December, 2015. As constraints, I will remove all foreign companies, investment trusts and other security types such as warrants, closed-end funds, global depository receipts (GDRs) and American Depository Receipts (ADRs). Foreign companies and investment funds were removed because they may display different trading behaviours (Angelidis, T., 2008). To attend to survivorship bias, I will use all companies in the LSE: active, dead and suspended. These initial restrictions imply an initial sample of 7214 firms. All the firms without DataStream Code were excluded, since the absence of this code is related with lack of information. I exclude the financial firms (banking, insurance, real estate and trading) because the model applied to estimate earnings quality does not reflect their activities. Similarly, gas and electricity firms were also excluded. I required at least 8 years of complete data for the independent variable, eliminating the firms with missing values on this variable. For the dependent variable, firms with no observations were not considered. I ended up with a sample of 1722 firms, covering the period between 1988 and 2015.

Summarizing, the original sample comprises 7214 firms. After the application of the filters, the final sample consists of 1475 firms. To elucidate, Table 2 exposes the sample construction criteria, including the exclusions I used, individually mentioned.

Table 2: Sample Construction

The Table 2 shows the process used to build our sample, including all the exclusions applied to the initial sample. The exclusions are individually mentioned above.

| Initial Sample | 7214 Firms | |
|--|-------------------|---------------|
| Exclusion Criteria | Deleted Firms | Current Firms |
| Firms without DS Mnemonic Code | 1896 | 5319 |
| Financial Firms (2-Digit SIC Codes 60-67) | 613 | 4707 |
| Gas and Electricity (2-Digit SIC Code 49) | 69 | 4639 |
| Firms without at least 8 years of complete EQ data | 2917 | 1723 |
| Firms without return index data | 1 | 1722 |

| Final Sample | 1722 Firms |
|---------------------|-------------------|
|---------------------|-------------------|

All the financial and accounting data were obtained from Thomson Reuters DataStream. I will apply the daily return index instead of daily adjusted prices because the first variable is adjusted

for dividends and capital increases. The daily return index is collected in local currency (£). All collected stocks are value weighted. The proxy representing the risk free asset is given by the 1-Month Treasury Bill divided by the number of trading days.

At Table 3, we can realize the firm's distribution among the different industries. I organized the firms according to US four-digit SIC code, allocating them to one of the Fama and French's (1997) 49 industry groups.

Table 3: Firms Distribution

Table 2 shows the industry distribution of our sample. We follow the approach of Fama and French (1997), which organizes the firm between 49 industry groups. We used US four-digit SIC code.

| Industry Group | Industry Denomination | #Firms | %Firms | Industry Group | Industry Denomination | #Firms | %Firms |
|-----------------------|------------------------------|---------------|---------------|-----------------------|---|---------------|----------------|
| Industry 1 | Agriculture | 16 | 0,93% | Industry 22 | Electrical Equipment | 22 | 1,28% |
| Industry 2 | Food Products | 30 | 1,74% | Industry 23 | Automobiles & Trucks | 12 | 0,70% |
| Industry 3 | Candy & Soda | 11 | 0,64% | Industry 24 | Aircraft | 7 | 0,41% |
| Industry 4 | Beer & Liquor | 13 | 0,75% | Industry 25 | Shipbuilding, Railroad Equipment | 3 | 0,17% |
| Industry 5 | Tobacco Products | 3 | 0,17% | Industry 27 | Precious Metals | 59 | 3,43% |
| Industry 6 | Recreation | 17 | 0,99% | Industry 28 | Non-Metallic & Industrial Metal Mining | 51 | 2,96% |
| Industry 7 | Entertainment | 69 | 4,01% | Industry 29 | Coal | 13 | 0,75% |
| Industry 8 | Printing & Publishing | 29 | 1,68% | Industry 30 | Petroleum & Natural Gas | 86 | 4,99% |
| Industry 9 | Consumer Goods | 34 | 1,97% | Industry 32 | Communication | 37 | 2,15% |
| Industry 10 | Apparel | 16 | 0,93% | Industry 33 | Personal Services | 19 | 1,10% |
| Industry 11 | Healthcare | 8 | 0,46% | Industry 34 | Business Services | 384 | 22,3% |
| Industry 12 | Medical Equipment | 31 | 1,80% | Industry 35 | Computers | 40 | 2,32% |
| Industry 13 | Pharmaceutical Products | 43 | 2,50% | Industry 36 | Electronic Equipment | 53 | 3,08% |
| Industry 14 | Chemicals | 33 | 1,92% | Industry 37 | Measuring & Control Equipment | 26 | 1,51% |
| Industry 15 | Rubber & Plastic Products | 19 | 1,10% | Industry 38 | Business Supplies | 16 | 0,93% |
| Industry 16 | Textiles | 27 | 1,57% | Industry 39 | Shipping Containers | 4 | 0,23% |
| Industry 17 | Construction Materials | 61 | 3,54% | Industry 40 | Transportation | 47 | 2,73% |
| Industry 18 | Construction | 58 | 3,37% | Industry 41 | Wholesale | 87 | 5,05% |
| Industry 19 | Steel Works, Etc | 17 | 0,99% | Industry 42 | Retail | 110 | 6,39% |
| Industry 20 | Fabricated Products | 9 | 0,52% | Industry 43 | Restaurants, Hotels, Motels | 50 | 2,90% |
| Industry 21 | Machinery | 49 | 2,85% | Industry 49 | Firms not grouped in any other industry | 3 | 0,17% |
| Total | | | | 1722 | | | 100,00% |

The most significant industry group is Business Services (384 firms), which represents 22.30% of the sample. Retail is the second biggest group, followed closely by petroleum and natural gas industry, with approximately 6% (110 firms) and 5% (86 firms), respectively. The smallest industries are tobacco products, shipbuilding and railroad equipment and the firms not grouped in any other industry. Each one is composed by 3 firms, having a weight of 0.17% in the total sample. The average size of an industry group is 41 firms, which comprehends 2% of the sample. Belonging to the average industries, we have food products, printing and publishing, consumer goods, medical equipment, chemicals, textiles, communication, computers, measuring and control equipment.

4.2.Descriptive Statistics

Table 4 presents the descriptive statistics (Panel A) and the correlation matrix (Panel B) of the main items in this study. Panel A illustrates the standard deviation, mean, median, and the number of observations of the dependent, independent, and control variables. Panel B displays the correlations among all the variables of this study, and already described in section 3.

According to the data presented in the Panel A, the average annual idiosyncratic volatility is about 10%. On average, a firm has 17 years, having the oldest firm 52 years, since it was based in 1964. The firms included in our sample are relatively big, with an average size of 1.1 million pounds. The average firm has operating cash flows representing 0.7% of total assets, a financial leverage of 27% of total assets and a return on equity of -9%. In the Panel B is exposed the correlation matrix. Paying attention to the dependent variable, we notice that some correlations with the explanatory variables are quite strong, which give us a light on the possible signal about their relations. The coefficients of the correlation between the explanatory variables are not high, which is indicative of the non-existence of a possible multicollinearity problem. With a closer look, all the correlations are smaller than $|0.40|$. Succinct, with the data presented in the Table 4, we have a broad view of the firms' financial features.

Table 4: Summary Statistics and Correlation Matrix

Table 4 presents the descriptive statistics and the correlation matrix of our main variables: IVOL (idiosyncratic volatility), EQ (earnings quality), RET² (value relevant information), BTM (ratio book-to-market); CFO (earnings informativeness), AGE (firm age), LEV (leverage), NANAL (investor sophistication), ROE (operating performance), T. ASSETS (firm size) and RET (stock return performance). In Panel A are reported the standard deviation, mean and median, as well as the number of observations used in our regressions. In the Panel B, we illustrate the correlations between our dependent variable and the explanatory variables and among the explanatory variables.

Panel A: Summary Statistics

| | IVOL | EQ | RET ² | CFO | VCFO | BTM | T. ASSETS | LEV | RET | AGE | ROE | NANAL |
|---------------------|--------|--------|------------------|--------|--------|--------|-----------|---------|---------|---------|---------|--------|
| Mean | 0,0997 | 0,0634 | 0,3004 | 0,0074 | 0,2212 | 0,0009 | 1073270,0 | 0,2706 | -0,0265 | 16,8982 | -0,0905 | 5,8488 |
| Median | 0,0295 | 0,0029 | 0,0405 | 0,0692 | 0,0625 | 0,0005 | 45495,0 | 0,0469 | 0,0000 | 13,0000 | 0,0991 | 3,0000 |
| Std. Dev. | 0,6399 | 1,5540 | 0,9410 | 0,6116 | 4,2564 | 0,0050 | 7750549,0 | 19,7952 | 0,5462 | 12,8000 | 6,5862 | 6,1070 |
| Observations | 24118 | 22575 | 31336 | 23168 | 15485 | 24110 | 25205 | 25187 | 32384 | 25890 | 22563 | 17055 |

Panel B: Correlation Matrix

| | IVOL | EQ | RET ² | CFO | VCFO | BTM | T. ASSETS | LEV | RET | AGE | ROE | NANAL |
|------------------------|---------|---------|------------------|---------|---------|---------|-----------|--------|--------|--------|--------|--------|
| IVOL | 1,0000 | | | | | | | | | | | |
| EQ | 0,1208 | 1,0000 | | | | | | | | | | |
| RET² | 0,2894 | 0,0952 | 1,0000 | | | | | | | | | |
| CFO | -0,2433 | -0,1803 | -0,1236 | 1,0000 | | | | | | | | |
| VCFO | 0,1611 | 0,2687 | 0,1188 | -0,2162 | 1,0000 | | | | | | | |
| BTM | 0,0473 | -0,0181 | 0,1200 | -0,0432 | 0,0841 | 1,0000 | | | | | | |
| T. ASSETS | -0,0524 | -0,0301 | -0,0382 | 0,0292 | -0,0640 | 0,0151 | 1,0000 | | | | | |
| LEV | -0,0315 | -0,0968 | 0,0007 | 0,0660 | -0,1698 | -0,0111 | 0,0735 | 1,0000 | | | | |
| RET | -0,3031 | -0,0467 | 0,0559 | 0,2162 | -0,0617 | 0,0389 | 0,0116 | 0,0039 | 1,0000 | | | |
| AGE | -0,1216 | -0,1188 | -0,1042 | 0,0992 | -0,1714 | -0,0043 | 0,1304 | 0,1573 | 0,0527 | 1,0000 | | |
| ROE | -0,0324 | -0,0160 | -0,0347 | 0,1306 | -0,0883 | -0,0031 | 0,0053 | 0,0168 | 0,0279 | 0,0263 | 1,0000 | |
| NANAL | -0,1577 | -0,0879 | -0,1057 | 0,1362 | -0,1794 | -0,0603 | 0,3740 | 0,3150 | 0,0571 | 0,2859 | 0,0333 | 1,0000 |

5. METHODOLOGY AND EMPIRICAL RESULTS

5.1. Cross-sectional Analysis

Even if the purpose of this work is to study a time series relationship between idiosyncratic volatility and earnings quality, it is important to first prove an association between the two variables at the cross section level. In order to do that, we will estimate a cross-section regression between idiosyncratic volatility and our accrual-based measure (earnings quality estimated according to the Modified Jones (1991) model) as follows, bearing in mind other variables that we believe affect the behaviour of idiosyncratic volatility. These control variables are already described in the section 3.

$$\begin{aligned} IVOL_{it} = & \alpha_0 + \alpha_1 EQ_{i,t-1} + \alpha_2 RET_{i,t-1}^2 + \alpha_3 NANAL_{i,t-1} + \alpha_4 CFO_{i,t+1} + \alpha_5 ROE_{i,t-1} \\ & + \alpha_6 VCFO_{i,t-1} + \alpha_7 BtM_{i,t-1} + \alpha_8 SIZE_{i,t-1} + \alpha_9 LEV_{i,t-1} + \alpha_{10} RET_{i,t} \\ & + \alpha_{11} AGE_{i,t} + \varepsilon_{it} \end{aligned} \quad (8)$$

EQ is the independent variable, measured according to the Modified Jones (1991) model and posteriorly adapted by Kothari. Following Rajgopal and Venkatachalam (2011), our independent variable is lagged one year to avoid capturing a mere contemporary relationship with the idiosyncratic volatility.

Table 5 describes the results of the previous equation. The results of the regression (8) with OLS follow closely our predictions. As expected, the coefficient of our earnings quality proxy is positive and statistically significant (at 1%). We proved a positive relationship between idiosyncratic volatility and earnings quality, implying that poorer earnings quality is related with greater idiosyncratic volatility. This confirms our first hypothesis. I introduce the firm age as control variable, and following my predictions, it is negatively related with our dependent variable (significant at 1%), suggesting that as firms ages, the idiosyncratic volatility decreases. Contrary to our predictions, the ratio book-to-market coefficients present a negative signal. This results may be due to particularities of our research design and different variables measurement procedures. Nonetheless, a research of Ali et al. (2003), when studying the arbitrage risk and the book-to-market anomaly, proved that the book-to-market effect affects positively stocks that face higher idiosyncratic volatility. This investigation is in line with our results. To underlie that, similar to Wei and Zhang (2006), we showed that weaker performances are linked with higher idiosyncratic volatility, since the return on equity and the earnings informativeness coefficients are negative.

Table 5: Cross Sectional Regression Analysis with OLS

Table 5 presents the results of the OLS regression on idiosyncratic volatility. The dependent variable is the variance idiosyncratic volatility. The yearly variance of returns is computed as the sample variance of monthly returns within a month. EQ is measured as the squared abnormal accruals of the Modified Jones (1991) Model with the adaption of Kothari. EQ with total accruals greater than 1 in absolute value were eliminated. The control variables are AGE (set to 1 in the year the firm is born and add 1 in the subsequent years), BTM (ratio between the book value of equity and the market value of equity), VCFO (standard deviation of cash flows from operations in a 5-year window), RET2 (annual buy and hold return), CFO (net income minus total accruals, divided by average total assets), LEV (ratio between long term debt and total assets), ROE (net income divided by total shareholders' equity), SIZE (natural logarithm of total assets), NANAL (number of analysts following) and RET (contemporaneous buy and hold return). A more detailed description is available on section 4. All variables are winsorized at 1% and 99%. The standard errors are presented in parentheses and the statistical significance are illustrated with the common symbols ***, ** and *, which denotes a significance at the 1%, 5% and 10% level, respectively.

| Variable | Coefficient |
|---------------------------|--------------------------|
| C | 0,450407 *** (0,029312) |
| EQ | 0,729199 *** (0,113963) |
| RET² | 0,165999 *** (0,006331) |
| CFO | -0,214917 *** (0,019996) |
| VCFO | 0,120926 *** (0,031343) |
| BTM | 57,11683 *** (4,084867) |
| SIZE | -0,029283 *** (0,002866) |
| LEV | 0,115908 *** (0,026557) |
| RET | -0,24208 *** (0,006494) |
| AGE | -0,00094 *** (0,000261) |
| ROE | -0,090014 *** (0,008606) |
| NANAL | 0,002292 *** (0,000825) |
| R-squared | 0,312200 |
| Adjusted R-squared | 0,311445 |
| F-statistic | 413,471600 |
| Prob(F-statistic) | 0,000000 |
| No. Obs. | 10032 |

These results highlight the importance of earnings quality in explaining the determinants of idiosyncratic volatility, even after controlling with a broad set of control variables, susceptible of affect its behaviour.

5.1.1. Firm Fixed Effects Analysis

Considering the concerns related with the temporal size of our sample, i.e., the existence of multiple observations for the same firm, we perform a year fixed effect analysis to mitigate that apprehension. The utilization of year dummies will help to capture the effect of aggregate trends. In unreported table, we proved that the introduction of the year dummies does not change our results, since the relationship between earnings quality and idiosyncratic volatility keeps positive and statistically significant (at 1% level).

5.2. Trend Analysis

5.2.1. Idiosyncratic Volatility Behaviour

Once we want to investigate if earnings quality is related with the time trend behaviour of idiosyncratic volatility, it is necessary to ascertain how idiosyncratic return volatility performs. So, since we already proved a firm-level association between earnings quality and idiosyncratic volatility, we will study the idiosyncratic volatility behaviour. In this subsection we will try to prove that the trend in earnings quality affects the trend in idiosyncratic volatility. In the Figure 1, we can see the performance of idiosyncratic volatility between 1988 and 2015. At first glance, we perceive periods of relative high variances, followed by periods of small variances, which is in line with the investigation of Bekaert et al. (2012). Yet, at a closer look, we can figure an upward trend in the variable, even if small, in a broad sense. If we attend to specific period intervals, the pattern in the figure is very similar to the one presented in the US market. Analysing the works of Brandt et al. (2010), Zhang (2010), Chen et al. (2010), and Bekaert et al. (2012), applied to the United States, we can state that the American market shows an upward trend till 2000, a downward trend between 2001 and 2007, and an upward trend after that. So, if we broke our sample into smaller periods, with breaks in 2000, 2006 and 2009¹⁶, we can see that the episodic phenomenon in idiosyncratic volatility is also applied to the London market.

The Figure 1 illustrates the idiosyncratic volatility performance. Panel A represents the variable behaviour when we comprehend all the sample period, whereas Panel B shows the idiosyncratic volatility behaviour but when the sample is fragmented into 4 sub periods, according to the structural breakpoints indicated in the Chow Test.

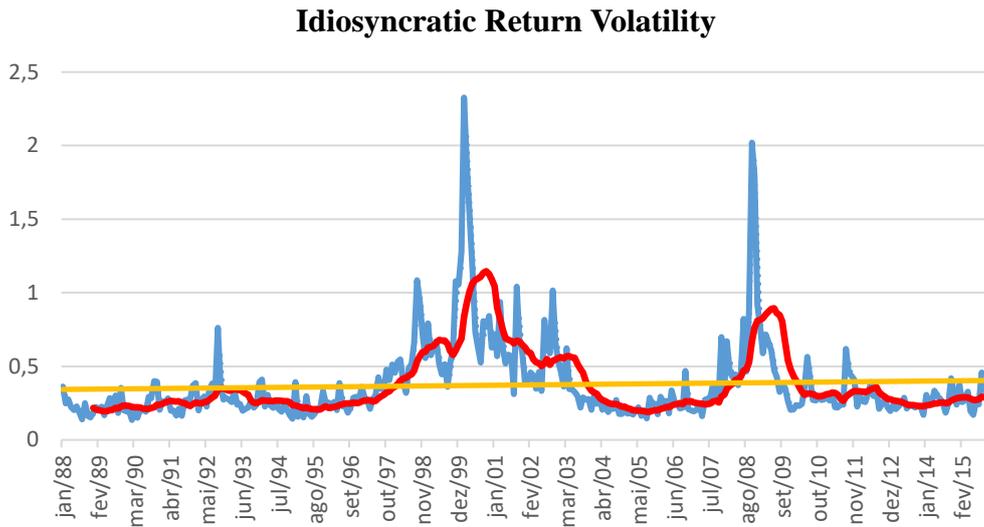
Analysing the figure 1, considering all the sample period, it is almost unperceivable the upward trend in idiosyncratic volatility. In fact, what is clear are the ebbs and flows in explicit points in time. However, when we cut the sample, limiting the periods to specific years, we can see that idiosyncratic volatility displays some upward or downward trend. As in the investigation of Campbell et al. (2001), we can see an upward trend in the London market till the beginning of 2000. Considering the resulting patterns of the cut-offs, we will try to prove that the earnings quality can explain these ups and downs in idiosyncratic volatility during our sample period. In order to do that, we will test the presence of a time trend in idiosyncratic volatility, confirming the inferences resulting from the observation of the Figure 1.

¹⁶ Using Chow structural break test, we proved that 2000, 2006, and 2009 are structural break points. These results are not reported.

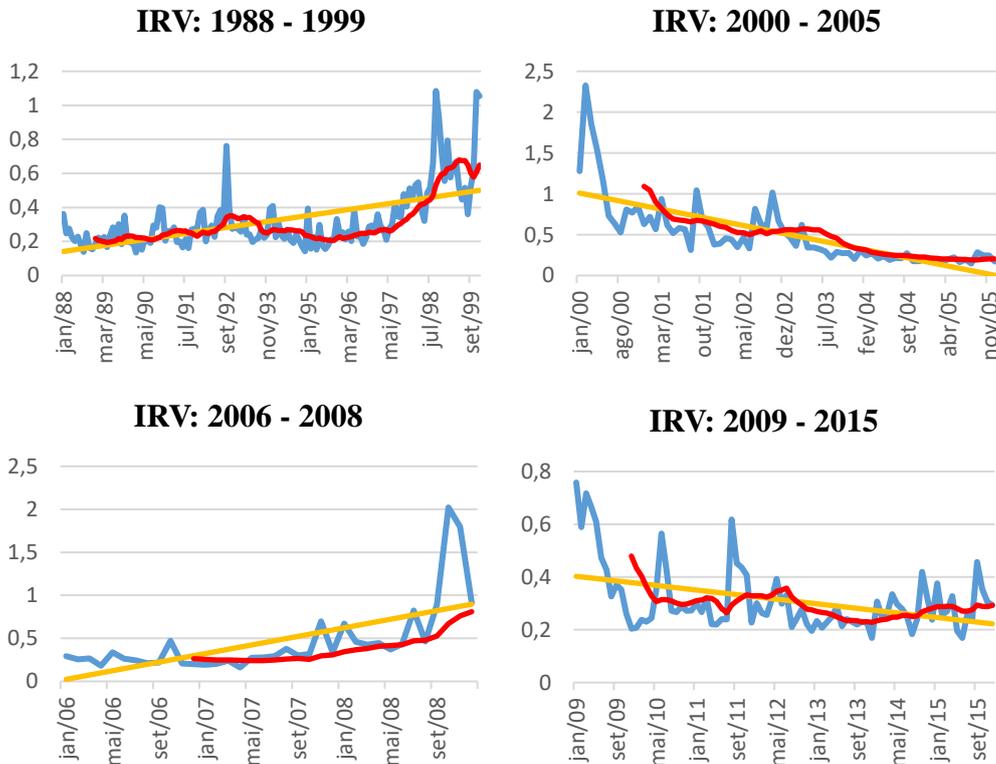
Figure 1: Idiosyncratic Volatility Behaviour

The Figure 1 shows the behaviour of average return volatility in two different perspectives. The idiosyncratic return volatility mentions to the average monthly variance estimated according to the CLMX model developed by Campbell, Lettau, Malkiel and Xu (2001). Panel A represents the performance of the variable when we comprehend all the sample period. Panel B shows the idiosyncratic volatility behaviour but when the sample is fragmented into 4 sub periods according to the structural breakpoints indicated in the Chow Test. For convenience, the idiosyncratic volatility is multiplied by 100. The red line represents the 12-month moving average of our variable, while the yellow line represents de linear trend.

Panel A: IRV trend behaviour between 1988 and 2015



Panel B: IRV trend behaviour across the sub periods



Similar to Brandt et al. (2010), the method used to estimate the time trend is:

$$IVOL_t = b_0 + b_1t + b_2IVOL_{t-1} + \varepsilon_t \quad (9)$$

IVOL is the average cross-section idiosyncratic volatility and *t* is the linear time trend variable.

Since we want to understand the pattern of idiosyncratic volatility and estimate its time trends across time, we will present five models, each one realizing five different time periods. Model 1 represents the complete sample, so *t* is in between 1988 and 2015. The other four models are divided according with the breaks identified in the Chow Test.

Table 6: Trend Tests

Table 6 reports the idiosyncratic volatility trend estimates, using monthly time series data. The idiosyncratic volatility measure is computed through the CLMX methodology. Excluding the Model 1 that covers all the sample period, the other models represent sub periods, according with the structural breaks identified with the Chow Test. Model 2 comprehends the period between 1988 and 1999, Model 3 comprises the sample period between 2000 and 2005, Model 4 studies the trend covering the years between 2006 and 2008, and the remaining years are included in the Model 5. The standard errors are presented in parentheses and the statistical significance are illustrated with the common symbols ***, ** and *, which denotes a significance at the 1%, 5% and 10% level, respectively.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---------------------------|----------------------------|----------------------------|-----------------------------|----------------------------|----------------------------|
| | 1988-2015 | 1988-1999 | 2000-2005 | 2006-2008 | 2009-2015 |
| Variable | Coefficient | Coefficient | Coefficient | Coefficient | Coefficient |
| C | 0,000668 *** (0,00021) | 0,000308 (0,000206) | 0,011454 *** (0,003687) | -0,026220 ** (0,012736) | 0,002529 ** (0,001323) |
| T | 3,15E-07 (9,23E-07) | 9,09E-06 *** (2,68E-06) | -5,33E-05 *** (1,83E-05) | 0,000122 ** (5,62E-05) | -4,86E-06 (4,09E-06) |
| IVOL_{t-1} | 0,806616 *** (0,032461) | 0,710659 *** (0,064868) | 0,613632 *** (0,095514) | 0,529628 *** (0,146863) | 0,632721 *** (0,071170) |
| R-squared | 0,651775 | 0,646965 | 0,720847 | 0,580049 | 0,586615 |
| Adjusted R-squared | 0,649677 | 0,641921 | 0,712756 | 0,554598 | 0,576408 |
| F-statistic | 310,702900 | 128,280400 | 89,088280 | 22,790310 | 57,471710 |
| Prob(F-statistic) | 0,000000 | 0,000000 | 0,000000 | 0,000001 | 0,000000 |
| No. of Obs. | 335 | 143 | 72 | 36 | 84 |

Therefore, Model 2 will be used to analyse the trend between 1988 and 1999, in Model 3 the sample period will vary between 2000 and 2005, Model 4 represents the period between 2006 and 2008, and the Model 5 will test the trend between 2009 till 2015. To estimate these models, we will use OLS. The table 6 shows the results.

In a broad sense, we can see that the sample shows an upward trend. In Model 1, the linear trend coefficient equals 3.15E-07, however, as expected, this trend is not significant. But when we split the sample and study specific time periods, the result changes. In fact, in Model 2, representative of the sample period between 1988 and 1999, the time trend coefficient *t* has a

positive value ($t = 9,09E-06$) and statistically significant at 1%. This model reinforces the results of Campbell et al. (2001). In turn, the Model 3 has a negative time trend coefficient ($t = -5.33 E -05$) and statistically significant at 1%. With these first two models, we extend to the English market, the results of Brandt et al. (2010), applied to the American market, which confirms that the rising trend in idiosyncratic volatility reverses its behaviour. The results of the Model 4 further support the claim that close to financial crisis periods there is an evident increase in the stocks return. As we can see, in this model the linear trend coefficient is positive ($t = 0.000122$) and statistically significant at 5%, what is in conformity with the results of Chen et al. (2012). Finally, Model 5 confirms a new reversal in the trend, since the linear trend coefficient presents a negative value ($t = -4.86E-06$), although not statistically significant.

With these outcomes, we empirically confirmed the conclusions drawn through the observation of the graphs in Figure 1. Thus, we can assert that the idiosyncratic volatility does not have an infinite increasing trend, but behaves as an episodic phenomenon, reversing, for any reason, the upward time trend, as secured by Brandt et al. (2010).

5.2.2. Earnings Quality Trend and Idiosyncratic Volatility Trend

At this point, we will focus on the trend analysis of our two key variables, since we had already established a firm-level association between earnings quality and idiosyncratic return volatility.

To study the relationship between the trend in earnings quality and the trend in idiosyncratic volatility, we will follow the approach used by Chen et al. (2011):

$$\overline{IVOL}_t = b_0 + b_1 t + b_2 \overline{X}_{t-1} + \varepsilon_t \quad (10)$$

This methodology is based in the cross-sectional means. Therefore, *IVOL* is the average cross-section idiosyncratic volatility, *t* is the time trend variable, and *X* represents the cross-sectional average of the variables we want to use to prove a time trend relationship with idiosyncratic volatility. In our case, *X* represents the earnings quality variable. The idea behind this model is that if the idiosyncratic volatility shows a time trend behaviour, it should be captured by the time trend variable *t*. Nonetheless, if others trend variables are included in our sample, and they also explain the trend in idiosyncratic volatility, the inclusion of these variables in our model will affect the power of the time trend coefficient *t*, weakening it. We will try to prove that earnings quality is one of these trending variables.

Table 7: Idiosyncratic Volatility Trend and Earnings Quality

Table 7 reports the idiosyncratic volatility trend estimates, using yearly time series data. The idiosyncratic volatility measure is computed through the CLMX methodology. $IVOL_t$ is the cross-sectional average of idiosyncratic volatility at the year t . EQ_{t-1} is the cross sectional average of earnings quality at year t . t is a time-varying variable, varying between 1989 and 2015. Excluding the Model 1 that covers all the sample period, the other models represent sub periods, according with the structural breaks identified with the Chow Test. Model 2 comprehends the period between 1988 and 1999, Model 2 comprises the sample period between 2000 and 2005, Model 3 studies the trend covering the years between 2006 and 2008, and the remaining years are included in the Model 4. Separator A only includes the time-varying variable t , while separator B adds the variable EQ . The standard errors are presented in parentheses and the statistical significance are illustrated with the common symbols ***, ** and *, which denotes a significance at the 1%, 5% and 10% level, respectively.

| Variable | Model 1 1988-2015 | | Model 2 1988-1999 | | Model 3 2000-2005 | | Model 4 2006-2008 | | Model 5 2009-2015 | |
|---------------------------|---------------------------|------------------------|---------------------------|------------------------|----------------------------|---------------------------|-------------------------|-----------------|---------------------------|-------------------------|
| | A | B | A | B | A | B | A | B | A | B |
| C | 0.013307 ** (0.005762) | 0.007912 (0.010850) | 0.004439 (0.003373) | 0.001017 (0.006727) | 0.174961 ** (0.045842) | 0.157103 * (0.059072) | -0.504508 (0.204816) | -0.204505 NA | 0.059651 ** (0.021257) | 0.052829 (0.033115) |
| t | x0.000138 (0.000366) | 1.00E-05 (0.000410) | 0.001273 ** (0.000519) | 0.001163 (0.000842) | -0.010569 ** (0.003140) | -0.010237 * (0.003489) | 0.028045 (0.010770) | 0.016365 NA | -0.002057 * (0.000883) | -0.001860 (0.001186) |
| EQ_{t-1} | | 1.964416 (2.704784) | | 1.082345 (2.347849) | | 3.812821 (6.634126) | | -16.53268 NA | | 0.522575 (1.786082) |
| R-squared | 0.005402 | 0.023275 | 0.375317 | 0.384507 | 0.739088 | 0.764966 | 0.871485 | 1.000000 | 0.520625 | 0.619690 |
| Adjusted R-squared | -0.032851 | -0.058119 | 0.312849 | 0.230633 | 0.673860 | 0.608277 | 0.742970 | NA | 0.424750 | 0.429535 |
| F-statistic | 0.141225 | 74.82677 | 6.008116 | 41.08930 | 11.33086 | 19.01113 | 6.781181 | NA | 5.430240 | 3.258868 |
| Prob(F-statistic) | 0.710115 | 0.285957 | 0.034191 | 2.498850 | 0.028144 | 4.882069 | 0.233417 | NA | 0.067187 | 0.144636 |
| No. Obs. | 28 | 28 | 12 | 12 | 6 | 6 | 3 | 3 | 7 | 7 |

Table 7 shows the results of the tests on the equation 10, where we applied the OLS estimation method. For each group, Panel A represents the time trend behaviour of idiosyncratic volatility, while the Panel B introduces the earnings quality variable.

As we can see, when we consider the full sample model, the trend behaviour in idiosyncratic volatility is explained by the behaviour of earnings quality. Despite the results are not being significant, we can see a reduction on the power of our time trend variable t , from 0.000138 to 0.00001, when we introduce the other trending variable, in this case, earnings quality. So, in a broad sense, the Model 1 tells us that the time trend behaviour in idiosyncratic volatility is explained by the time trend in earnings quality. With these results we confirm our *Hypothesis 2*, which says that earnings quality is related with the global tendency in idiosyncratic volatility.

When we split the sample in sub periods according to the Chow test, our results should be interpreted with caution. Remind that our sub models proved that the behaviour of idiosyncratic volatility is not constant. It shows an increase trend between 1988 and 1999, a decrease between 2000 and 2005, a new increase between 2006 and 2008 and decrease again after 2009.

In Model 2, the linear trend coefficient in Panel A equals 0.001273, and, as expected, we verified a decrease in the power of the time trend idiosyncratic volatility variable in the Panel B, measuring 0.001163. This model has a time period similar to Rajgopal and Venkatachalam (2011) research, so our outcome confirms their results and states that till 2000 earnings quality can explain the upward trend in idiosyncratic volatility. In the model 3, we can see that the time trend variable also loses power when earnings quality is added to the model, since it changes from -0.010569 to -0.010237, Panel A and B, respectively. So, for this sub period the trend in earnings quality explains the trend in idiosyncratic volatility. Note that the Model 3 represents a time period in which idiosyncratic volatility has a decreasing trend, and that fact is highlighted by the t negative coefficient. In the Model 4, it is difficult to interpret the results since our sample is only composed by three observations. However, the results follow again the expected since the time trend variable loses power (it goes from 0.02845 to 0.016365). In model 4, we confirm the results of Chen et al. (2012), since he proved a rise in idiosyncratic volatility near the recent financial crisis, as well as the influence of earnings quality in idiosyncratic volatility behaviour during that time. In Model 5, the conclusions are in line with the ones we took from the Model 3. With these results we confirm the *Hypothesis 3*, since our variable also explains the episodic trends in idiosyncratic volatility. Thus, as Chen et al. (2012), but applied to the

London market, we proved that earnings quality can explain the overall trend in idiosyncratic volatility and the episodic reversals.

Just to underline that in every subsample, the signal of the time trend coefficient t is in accordance with the ups and downs of the volatility. When the idiosyncratic volatility is increasing, t is positive, and when it is decreasing t is negative, i.e., it is positive between 1988 and 1999 and between 2006 and 2008, and it is negative between 2000 and 2005 and between 2009 and 2015. These reversals are in line with the Campbell et al. (2001), Brandt et al. (2010), and Chen et al. (2012) researches.

6. CONCLUSIONS

Studies on the idiosyncratic volatility have assumed greater importance in recent years. First the puzzle of idiosyncratic volatility and more recently its behaviour over time. Taking into account this last aspect, this study aims to verify, through a time trend analysis, if the behaviour of idiosyncratic volatility over time is related with reporting quality. This study includes 1722 firms from the London Stock Exchange and a time period between 1988 and 2015. Idiosyncratic volatility was determined according to the CLMX model developed by Campbell, Lettau, Malkiel and Xu, in 2001. Earnings quality, a measurement based on accrual, was determined according to the Modified Jones (1991) Model with an adaptation of Kothari (2005). For this study we used ten control variables to mitigate the effect of possible omitted variables.

At first, we showed that, in fact, the idiosyncratic volatility is positively related to earnings quality, even after the use of several control variables. This means that lower financial information quality implies greater volatility idiosyncratic. After establishing a cross-sectional relationship between the two variables, in a second moment we focused on the idiosyncratic volatility behaviour analysis over time. We found that, in the London Stock Exchange, more than an upward trend over time, idiosyncratic volatility presents episodes where it reverses its behaviour. When we consider the full sample period, volatility has a slight upward trend, and this is explained by earnings quality. When we divide the sample and study the sub periods created separately, following our expectations, earnings quality can explain these ebbs and flows in idiosyncratic volatility. Subsequently, this research confirms the results of Rajgopal and Venkatachalam (2011), since we also prove that there is an upward trend in idiosyncratic volatility between 1988 and 1999 in which its trend is explained by the behaviour of earnings

quality. Also highlight that before the financial crisis, our levels of idiosyncratic volatility rise, as in Chen et al. (2012), and this sudden rise can be explained by earnings quality.

With regard to the limitations and suggestions for future research, it would be useful to use other proxies for earnings quality and idiosyncratic volatility, in order to test the sensitivity of our results. Another benefit would be to repeat this study for other markets and different time periods, or, as in similar studies that use monthly data, perform this study with a different data frequency to realize if the results maintain their robustness. It would also be interesting to know what other variables also affect idiosyncratic volatility over time, its trend and reversals. This would contribute to the enrichment of literature related to the study of idiosyncratic volatility. Taking advantage of the episode before crisis periods, it would be also important to ascertain the impact of the financial crisis on the behaviour of idiosyncratic volatility and what determines its reversal in periods prior to the financial collapse.

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