

Accruals Quality, Analysts' Forecasts and Idiosyncratic Return Volatility: UK Evidence

ABSTRACT

We investigate if accruals quality is useful for stock market investors as an indicator of earnings quality, by examining its association with idiosyncratic return volatility, for a sample of UK firms listed on the London Stock Exchange.

Using panel data, we find that poor accruals quality is statistically associated with higher firm-specific return volatility. This association also holds for other measures used for the quality of the information environment: dispersion in analysts' forecasts, the innate component of accruals quality, which reflects the uncertainty about the nature of the firm's business and the discretionary component of accruals quality, which is related to managerial discretionary choices. More specifically, we find that adding the dispersion in analysts' forecasts increases the explanatory power for idiosyncratic volatility of the remaining measures of the quality of the information environment. Our results are consistent with the noise-based approach of idiosyncratic volatility. These findings are likely to contribute to the debate on whether idiosyncratic return volatility captures more firm-specific information being impounded into stock prices or essentially reflects noise.

JEL Classification: G12, G14, M40

Keywords: Idiosyncratic Volatility, Accruals Quality, Analysts' Forecasts.

1. INTRODUCTION

A growing literature exists in finance and accounting aiming to explain the findings reported in the seminal work of Campbell et al. (2001) which documents a noticeable increase of aggregate idiosyncratic return volatility relative to aggregate market volatility over the period from 1962 to 1997.

Our paper examines the cross-sectional association between firm-specific volatility in stock returns and the quality of a firm's information environment, more specifically we analyze whether idiosyncratic return volatility (IVOL) is related to a number of proxies for the quality of a firm's information environment.

This research is in line with the study of Rajgopal and Venkatachalam (2011) that find evidence on the association between higher levels of IVOL and deteriorating financial reporting quality across time and the results of Chen et al. (2012) showing that the time series variation in idiosyncratic return volatility is attributable to discretionary accrual volatility.

Identifying the determinants of idiosyncratic volatility has been a topical issue for investors, managers, regulators, accountants and academics. Moreover, the stream of literature on the nature of IVOL has important implications for asset pricing models. In some of these models, the variance of stock returns can be decomposed into systematic variance and idiosyncratic variance. Both components have been studied in prior literature, yet firm-specific variance has received far less attention because the prevalent theory assumes it can be eliminated in a well-diversified portfolio. However, because of specific constraints or by choice, for example due to corporate compensation policies (Campbell et al., 2001), some investors hold portfolios that are not well diversified and thus they are affected by shifts in idiosyncratic volatility as well as by shifts in market volatility, Xu and Malkiel (2003). Furthermore, investors using arbitrage strategies to exploit the mispricing of individual stocks, whose activity is fundamental to the efficiency of stock markets, face risks related to idiosyncratic volatility.

By studying the association between IVOL and the quality of a firm's information environment we also aim to contribute to a topical research question that is whether IVOL captures the aggregation of firm-specific information into stock prices or essentially reflects noise. A strand of literature analyzes the association between firm-specific volatility and the characteristics of the firm's information or governance environment. However, these studies differ in the assumption about whether IVOL captures firm-specific information or noise, Li et al. 2014. Prior studies beginning with Roll (1988) report a modest ability of asset pricing models to explain stock price variations even after eliminating data surrounding news reports in the financial press. Therefore, beyond the econometric definition of idiosyncratic volatility there is no consensus in the literature about whether firm-specific volatility can be explained by the capitalization of private information or by noise. Among those who develop the private information explanation, Morck et al. (2000) propose that stock markets in developed economies tend to capitalize more firm-specific information, thus exhibiting high levels of IVOL. In the same vein, Ferreira and Laux (2007) use IVOL to measure firm-specific information impounded into stock prices and Hutton et al. (2009) relate less firm-specific information available with less IVOL. In the strand of literature related to explanations based on noise trading and poor information environments, Rajgopal and Venkatachalam (2011) find empirical results indicating a positive association between rising IVOL and falling earnings quality and Kelly (2014) provides empirical evidence that high IVOL stocks are small, young, followed by few analysts and have high bid-ask spreads, and these

characteristics, which reflect a poor information environment, do not facilitate the incorporation of private information into stock prices. In the same line of research, Aabo et al. (2017) find that larger values of IVOL reflect a high level noise trading.

Accounting fundamentals are extensively used to develop measures of earnings quality in a number of research studies including those relating to IVOL, for example Hutton et al. (2009), Rajgopal and Venkatachalam (2011) and Chen et al. (2012). In this research, we examine the relationship between idiosyncratic volatility and three accrual-based measures for earnings quality that are accruals quality and the innate and discretionary components of accruals quality. Accruals quality is used for example by Francis et al. (2005), Bhattacharya et al. (2013) and Cerqueira and Pereira (2017). In addition, Francis et al. (2005) decomposes the accruals quality measure to investigate whether the cost of capital is related to the innate and the discretionary components of accruals quality.

We also add another measure of the quality of the firm's information environment that is the dispersion in analysts' forecasts. We propose that combining the accrual-based measures of earnings quality and the dispersion in analysts' forecasts provides a better indicator of the quality of a firm's information environment than accruals quality measures solely and our results support this hypothesis.

Using daily data on stock returns for UK firms listed on the London Stock Exchange, we find a positive association between poor information environments and idiosyncratic volatility. These results are consistent with noise view of idiosyncratic volatility and are in line with the findings of Rajgopal and Venkatachalam (2011).

As regards the determinants of IVOL, we find evidence that poor information environment, leverage and the intensity of information disclosure tend to increase IVOL, while more age, better performance and larger firms tend exhibit lower levels of IVOL.

Our contribution to the literature on the quality of a firm's information environment and idiosyncratic volatility is threefold. Firstly, using UK nonfinancial firms listed in the London Stock Exchange, we provide empirical evidence on the positive association between poor information environments and idiosyncratic volatility. This finding is important because it provides insights into the interpretation of the residuals of asset pricing models, namely because these results contrast with the traditional view where such residuals reflect the incorporation of firm-specific information into stock prices. Secondly, our study uses UK data. The United Kingdom has the most developed financial market in Europe and it is important to compare our results with those of related studies for the US, namely with the studies of Rajgopal and Venkatachalam (2011) and Chen et al. (2012). Thirdly, the studies of Rajgopal and Venkatachalam (2011) and Chen et al. (2012) use sample periods ending in 2001 and 2009 respectively, while ours ends in 2015, thus we include more years after the 2008 financial crisis. Although we do not compare the results before and after the crisis it is important to incorporate in the analysis data obtained in distinct financial scenarios.

The remainder of this article is organized as follows. Section 2 displays a brief literature review and develops the hypotheses tested in the empirical study. Section 3 describes the empirical research design. Section 4 presents sample selection procedures and sample characteristics. Section 5 documents some descriptive statistics and reports the results of the empirical tests and in Section 6 are presented some concluding remarks.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Based on asset pricing models, idiosyncratic volatility measures the part of the variation in returns after adjusting total risk for the variation in non-diversifiable risk factors included in a specific asset pricing model, for example the CAPM.

Standard asset pricing models consider that only systematic risk is priced in equilibrium, because in theory idiosyncratic risk can be eliminated by portfolio diversification.

However, recent literature claims that investors hold poorly diversified portfolios due to transaction costs, taxes or other institutional restrictions, Angelidis and Tessaromatis (2008). Additionally, empirical findings of Goetzman and Kumar (2008) document that a large proportion of a sample of US individual investors hold under-diversified portfolios including less than ten stocks. This contrasts with the evidence reported by Campbell et al. (2001) that the increase in idiosyncratic volatility over time has increased the number of stocks needed to achieve portfolio diversification to at least fifty stocks. Once some investors hold non-diversified portfolios then idiosyncratic risk should matter to explain stock returns and asset pricing models that include only common systematic risk-factors could be miss-specified.

In line with the above arguments, previous studies have argued that idiosyncratic volatility can reflect either the capitalization of firm-specific information into stock prices, Morck et al. (2000), Ferreira and Laux (2007) and Hutton et al. (2009) or noise, namely poor earnings quality, Rajgopal and Venkatachalam (2011) and Chen et al. (2012), retail investors behaving as noise traders, Foucault et al. (2011) or the increasing role of noise trading, Aabo et al. (2017). A number of prior studies find that idiosyncratic volatility displays a positive and significant relationship to mispricing, consistent with the noise approach to idiosyncratic volatility, Li et al. (2014).

We assume that poor information environments make more difficult for investors to interpret information contained in reported earnings and thus investors with no access to private information tend to trade on such poor public information. With poor public information informed investors get an informational advantage relative to liquidity traders, O'Hara's (2004). Thus, the characteristics of the trading process must reflect investors' heterogeneous beliefs. In line with the above argument, Foucault et al. (2011) find that, on average, stocks purchased by retail investors underperform stocks sold by retail investors, suggesting that those investors tend to trade for non-informational reasons. Given that such trading can move stock prices, the corresponding change in stock returns is likely to reflect, at least in part, noise.

Despite this recent trend in the literature supporting the noise hypothesis of IVOL, whether IVOL captures firm-specific information or noise remains an empirical question and, following the noise approach to IVOL, we posit the following hypothesis:

H1: Poor information environments are positively associated with idiosyncratic return volatility.

To develop further our research questions we must say that our first proxy for the quality of information environment is accruals quality, widely adopted in extant literature to measure earnings quality such as Francis et al. (2005) and Rajgopal and Venkatachalam (2011). In addition, following Francis et al. (2005) and Lobo et al. (2012) we further separate total accruals quality into an innate component and a discretionary component. Innate accruals quality is the component that captures uncertainty about the nature of the firm's business and discretionary accruals quality reflects managerial accounting discretion and error, Lobo et al. (2012). Evidence in Bhattacharya et al. (2013) is consistent with both the innate and discretionary accruals quality being associated with greater information asymmetry. Lobo et

al. (2012) find lower consensus (more dispersion in beliefs) for firms with both lower innate and discretionary accruals quality, meaning that both could be used as inverse proxies for the quality of information environment. Furthermore empirical evidence reported by Francis et al. (2005) and Lobo et al. (2012) are consistent with a stronger impact of the innate component relative to the discretionary component on the dependent variables under study. Thus, we decompose our first hypothesis:

H1a: Poor accruals quality is positively associated with idiosyncratic return volatility.

H1b: Poor innate accruals quality is positively associated with idiosyncratic return volatility

H1c: Poor discretionary accruals quality is positively associated with idiosyncratic return volatility

H1d: The association between poor innate accruals quality and idiosyncratic volatility is stronger than the association between discretionary accruals quality and idiosyncratic volatility.

Usually poor accruals quality measures are associated with poor information environments. However, accrual accounting is assumed to provide a better basis for assessing the entity's past and future performance than information solely about cash flows. Therefore, another stream in literature argues that measures based on abnormal accruals convey value relevant information to outside investors. For example Badertscher et al. (2012), Chen et al. (2013) and Cerqueira and Pereira (2015) argue that managers may use discretionary accounting choices to communicate their private information about a firm's future performance. Therefore, accruals based measures may be noisy indicators of a firm's information environment quality.

We further develop a method to enhance the discriminatory power of accrual-based measures of earnings quality by taking into account the dispersion in financial analysts' forecasts. Because analysts follow all information disclosed by the firm then their forecasts must reflect the convergence between information provided in reported earnings and other pieces of information about the firm. Therefore, poor accruals quality associated with a high dispersion in analysts' forecasts may indicate firms with a poor information environment, Cerqueira and Pereira (2017).

We propose that managers with no opportunistic incentives to manage earnings disclose additional information when the uncertainty in the nature of the firm's business or accounting choices result in a poor information environment. This means that in this case managers use all means to communicate the true firm performance to investors, thus reducing heterogeneity in analysts' beliefs about the performance of the firm. Thus, we propose that combining either of the three measures of accruals quality and the dispersion in analysts' forecasts provides a better indicator about the quality of a firm's information environment than the accrual-based measures solely and we posit the following hypothesis:

H2: The positive association between poor information environments and idiosyncratic return volatility is stronger for firms with poor accruals quality (innate accruals quality, discretionary accruals quality) and a high dispersion in analysts' forecasts.

Once accruals quality reflects the volatility of abnormal accruals we propose that high volatilities are likely to identify firms with poor information environments and consequently high levels of firm-specific volatility. Thus, the association between accruals quality and idiosyncratic volatility is expected to be stronger for firms with worst earnings quality

anticipating a nonlinear relationship between accruals quality and idiosyncratic volatility, leading to the following hypothesis:

H3: The positive association between poor accruals quality and idiosyncratic return volatility is nonlinear and such association is stronger for firms with the worst accruals quality.

3. EMPIRICAL RESEARCH DESIGN

3.1. DEPENDENT VARIABLE

3.1.1. IDIOSYNCRATIC VOLATILITY

Idiosyncratic volatility has been widely used as a measure of idiosyncratic risk. Two approaches can be used to estimate the idiosyncratic volatility: direct decomposition method and indirect decomposition method, Xu and Malkiel (2003). The direct decomposition method estimates idiosyncratic volatility as the variance of the residuals of an asset pricing model, such as the CAPM or the Fama and French Three-Factor Model. The indirect decomposition Method developed by Campbell et al. (2001) yields a weighted average of firm-level volatility across firms. Because we are interested in the cross-sectional relation between IVOL and the quality of information environment at the firm level, and not in the aggregate volatility, we use the direct method, Ang et al. (2006), Rajgopal and Venkatachalam (2011), and Hou and Loh (2016).

For each firm and month, we obtain the residuals from the regression of a firm's daily returns on the Capital Asset Pricing Model, requiring that stock returns of the firm are available for at least twelve trading days over the month.

The regression equation estimated monthly is as follows,

$$r_{i,t} = r_{f,t} + \beta_i \times (r_{m,t} - r_{f,t}) + e_{i,t}$$

Where $r_{i,t}$, $r_{m,t}$ and $r_{f,t}$ represent, respectively, the daily return of the stock, of the market and the risk free rate. The beta of the stock i , β_i , used in estimations is obtained on an annual basis given by the average of monthly betas. Furthermore, we assume that the daily risk-free rate is given by the three month government bond return divided by the number of trading days. When the information on government bonds is not available on Datastream we use the interbank lending rate Libor.

We compute annual idiosyncratic variance by multiplying the variance of daily residuals by the number of trading days in the year.

3.2. INDEPENDENT VARIABLES

3.2.1. ACCRUAL-BASED MEASURES

The first measure of the quality of information environment is accruals quality which is given by the standard deviation of the residuals of the regression of total accruals on a number of explanatory variables. We use the accruals quality metric developed by Dechow and Dichev (2002), as modified by McNichols (2002) and used in prior literature, for example Francis et al. (2005). Dechow and Dichev (2002) measure the quality of accruals by the extent to which current accruals map into past, current and future cash flows, more specifically by the standard deviation of the residuals of the regression of current accruals on cash flows (estimated at the firm level or at the sector level). McNichols (2002) include in the estimation of residuals the variables current year

property, plant and equipment and change in net sales, which are the fundamental variables in the Jones (1991) model. Francis et al. (2005) investigate the impact of this measure on the cost of capital. Specifically they estimate the regression residuals cross-sectionally, by year, within each of the 48 Fama and French (1997) industry classifications.

To measure accruals quality, we begin by computing total current accruals as the change in noncash working capital,

$$TCA_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STDebt_{i,t} \quad (1)$$

Where ΔCA is the change in current assets, ΔCL is the change in current liabilities, $\Delta Cash$ is the change in cash, $\Delta STDebt$ represents the change in short term debt.

Accruals quality is measured by the standard deviation of the residuals obtained by regressing total current accruals on operating cash flow in the current period, prior period and future period, change in revenues and gross value of property plant and equipment.

$$TCA_{i,t} = \alpha_0 + \alpha_1 CFO_{i,t-1} + \alpha_2 CFO_{i,t} + \alpha_3 CFO_{i,t+1} + \alpha_4 PPE_{i,t} + \alpha_5 Rev_{i,t} + e_{i,t} \quad (2)$$

All variables are scaled by average total assets.

We estimate cash flow from operations as the difference between net income before extraordinary items and total accruals (TA),

$$CFO_{i,t} = NIBE_{i,t} - TA_{i,t} \quad (3)$$

Where TA is defined as the change in noncash working capital minus depreciation and amortization expense,

$$TA_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STDebt_{i,t} - Depn_{i,t} \quad (4)$$

In order to obtain the residuals $e_{i,t}$ for firm i and year t , equation (2) is cross-sectionally estimated in year t within each of the 48 Fama and French's (1997) industry classification. Accruals quality in year t refers to the standard deviation of a firm's residuals calculated over year $t-4$ through t .

We also decompose the accruals quality measure into an innate component and a discretionary component following the Francis et al. (2005) approach, based on annual cross-sectional estimations of the accruals quality measure on a number of explanatory variables that are measures for operating uncertainty such as the log of total assets, standard deviation of cash flow from operations (scaled by the average total assets) over the 10 years ending in year t , standard deviation of Sales (scaled by average total assets) over the 10 years ending in year t , log of operating cycle, where the operating cycle is calculated as $360 * (\text{Average Accounts Receivable} / \text{Sales}) + 360 * (\text{Average inventory} / \text{COGS})$ and the proportion of reported negative net income before extraordinary items over the past 10 years.

3.2. INDEPENDENT VARIABLES

3.2.2. DISPERSION IN ANALYSTS' FORECASTS

To further investigate the extent to which the quality of the firm's information environment affects IVOL we develop an approach that builds on the assumption that a high dispersion in analysts' forecasts is a signal of a poor information environment. This approach may be useful because accrual-based measures might be noise indicators of the quality of the information environment. We expect that by combining the accrual-based measures with the dispersion in analysts' forecast results in a stronger association between the quality of information environment and IVOL.

Our variable dispersion in analysts' forecasts (DISP) is a dummy variable building on the dispersion in analysts' forecasts. DISP is set equal to one for values of the dispersion in analysts' forecasts higher than the 33rd percentile and zero otherwise. The dispersion in analysts' forecasts is defined as the standard deviation in analysts' forecasts scaled by the median forecast. Because analysts follow all information disclosed by the firm then their forecasts must reflect the convergence between information provided in reported earnings and other pieces of information about the firm. Therefore, the positive association between poor accrual-based measures and IVOL may be stronger for firms with a high dispersion in analysts' forecasts.

3.3. EMPIRICAL MODELS AND CONTROL VARIABLES

In this section, we develop the empirical models used to investigate the association between the quality of information environment and idiosyncratic volatility. In this model, in a first equation we use the accruals quality measure (AQ) as the main independent variable. In a second equation of this model, we include in the regression the innate component of accruals quality instead of AQ. In a third equation we include the discretionary component of accruals quality instead of AQ. In a fourth regression we combine both the innate and discretionary components of accruals quality. Previous studies identify a number of variables that affect idiosyncratic volatility. Thus, including accruals quality and control variables we get the following cross-sectional regression,

$$\begin{aligned}
 IVOL_{i,t} = & \alpha_0 + \alpha_1 AQ_{i,t-1} + \alpha_2 AGE_{i,t} + \alpha_3 BM_{i,t-1} + \alpha_4 VCFO_{i,t-1} \\
 & + \alpha_5 RET_{i,t-1}^2 + \alpha_6 LEV_{i,t-1} + \alpha_7 ROE_{i,t-1} + \alpha_8 SIZE_{i,t-1} \\
 & + \alpha_9 RET_{i,t} + e_{i,t}
 \end{aligned} \tag{5}$$

IVOL is the annual idiosyncratic volatility as defined above.

AQ is the accruals quality measure given by the standard deviation of residuals from Francis et al. (2005) regression model, also defined above. We expect to find higher levels of idiosyncratic volatility for firms with poor information environment. If poor accruals quality indicates poor information environment then a positive sign is expected for the AQ regression coefficient. We use the lagged variable AQ in order to avoid possible endogeneity problems in the sense that certain firm characteristics that affect AQ might also affect IVOL. AGE represents firm age calculated as one plus the difference between current year and the firm's base date. The variable "base date" in Thomson Reuters Datastream is used as a proxy for a firm's age. Base date is the date from which Datastream holds information about the

issue; for the UK the base date is one day before trading in the stock starts. Idiosyncratic volatility increases with uncertainty about the firm's average profitability and, therefore, tends to be higher for younger firms, Pastor and Veronesi (2003) and Fink et al. (2010). Thus, it is expected that idiosyncratic return volatility will be inversely related to the firm's age.

BM is another control variable for IVOL indicating the level of growth opportunities. It is measured as the ratio between the book value of equity and the market value of equity. Brown and Kapadia (2007) and Cao et al. (2008) relate the increase in average idiosyncratic volatility to the increase in the level of growth opportunities. Larger book-to-market ratios are usually associated with less growth opportunities and Rajgopal and Venkatachalam (2011) suggest that firms with greater growth opportunities are likely to experience greater idiosyncratic return volatility. Since, the book-to-market variable is an inverse proxy for a firm's growth opportunities, it is expected a negative association between this variable and idiosyncratic volatility.

VCFO is the volatility of operating cash flows, measured for each firm-year as the variance of annual operating cash flow scaled by average total assets over the trailing five-year window. 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.

RET2 is the squared annual buy-and-hold return that is likely to capture the disclosure of other value-relevant information, Rajgopal and Venkatachalam (2011). More information disclosure by a firm is likely to increase return volatility.

LEV is measured by the ratio of long term debt on the book value of total assets. Following Ang et al. (2009), as leverage rises, the negative relation between idiosyncratic volatility and stock returns gets stronger. Since highly leveraged firms are more prone to financial distress, leverage may be positively related to stock return volatility, Rajgopal and Venkatachalam (2011).

ROE represents return on equity, measured by the ratio between net income and book value of equity. Following Wei and Zhang (2006), there is a negative statistical association between return on equity and stock return volatility, because low past earnings increases the uncertainty about a firm's future cash flows.

SIZE is measured by the natural logarithm of market capitalization. Several studies show that small firms tend to exhibit higher idiosyncratic volatility. This negative relation between the two variables is found across numerous stock markets, including the United States Pastor and Veronesi (2003), Bali and Cakici (2008) and Brown and Kapadia (2007), Japan (Chang and Dong, 2006) or Australia (Liu and Di Iorio, 2016).

RET is stock return performance measured as the contemporaneous annual buy-and-hold return. Evidence across several developed markets provided by Ang et al. (2009) shows that the difference in average returns across stocks with low and high IVOL is statistically significant. Additionally, the average return of stocks with the lowest IVOL exceeds the average return of stocks with the highest IVOL. Such evidence is consistent with a negative association between IVOL and average stock return performance.

To further investigate the extent to which the quality of the firm's information environment affects IVOL we develop an approach that builds on the assumption that a high dispersion in analysts' forecasts is a signal of a poor information environment. We expect that by combining accrual-based measures as proxies of the quality of information environment with the dispersion in analysts' forecast results in a stronger indicator of the quality of information

environment. In this second model, we also estimate four equations that include accruals quality, or the innate or/and the discretionary components of accruals quality.

$$\begin{aligned} IVOL_{i,t} = & \alpha_0 + \alpha_1 AQ_{i,t-1} + \alpha_2 DISP_{i,t-1} \times AQ_{i,t-1} + \alpha_3 AGE_{i,t} \\ & + \alpha_4 BM_{i,t-1} + \alpha_5 VCFO_{i,t-1} + \alpha_6 RET_{i,t-1}^2 + \alpha_7 LEV_{i,t-1} \\ & + \alpha_8 ROE_{i,t-1} + \alpha_9 SIZE_{i,t-1} + \alpha_{10} RET_{i,t} + e_{i,t} \end{aligned} \quad (6)$$

DISP is a dummy variable building on the dispersion in analysts' forecasts. DISP is set equal to one for values of the dispersion in analysts' forecasts higher than the 33rd percentile and zero otherwise.

4. DATA AND SAMPLE SELECTION

Our sample consists of UK firms listed in the London Stock Exchange, over the period from 1998 to 2015. Our primary source of data is the Thomson Reuters Datastream database. Additionally, we collect information on the standard deviation of analysts' earnings per share estimates from I/B/E/S.

In order to allow comparison we include in our sample firm-year observations if their financial reports are based on IFRS accounting standards. While the mandatory IFRS adoption for listed firms in European Union was made effective from 2005, many firms voluntarily adopt IFRS few years before. Thus, we also include in our sample years from 1998 to 2004, but in order to ensure that only firm-year observations reported under IFRS were included in estimations we use the Thomson Reuters Datastream key item Accounting Standards Followed.

We exclude firms with missing industry code classification, financial firms and utilities (Fama and French industry codes 31, 44, 45, 46, 47 and 48) because they are subject to specific regulations. Additionally, we use other procedures to remove from our data some of the errors that have been reported in earlier studies. For example, delisted firms show up in price records with a constant value, after delisting. Thus we identify those firms and delete all the latest observations that do not change over time. Another correction we make is to delete observations of daily prices that do not change over more than three consecutive months, and we define a number of different rules to identify outliers, for example log daily returns higher than 1.4 or lower than -1.4. For a firm to be included in the sample we require seven years with complete data because accruals quality is the standard deviation of the residuals obtained by regressing total current accruals on a firm's cash flows and other economic variables over five years. However, we need to consider two additional years because of the explanatory variables previous cash flow and future cash flow.

Regarding the number of firm-year observations it depends on the specific regression being estimated, because observations with missing values in the variables are not included.

5. EMPIRICAL RESULTS

5.1. DESCRIPTIVE STATISTICS AND CORRELATIONS

Table 1 gives descriptive statistics of the variables used to measure idiosyncratic return volatility, accruals quality and other explanatory variables for IVOL. To mitigate the effect of potential outliers, the variables are winsorized at the first and ninety-ninth percentile.

Table 1: Descriptive Statistics for Selected Variables

	Mean	Std. Dev.	Q1	Median	Q3
IVOL	0.272	0.357	0.066	0.139	0.319
AQ	0.064	0.060	0.026	0.045	0.079
AGE	17.261	14.130	6.000	12.000	26.000
BM	0.780	0.785	0.289	0.539	0.974
VCFO	0.227	0.736	0.003	0.011	0.069
RET2	0.319	0.615	0.020	0.095	0.308
LEV	0.116	0.166	0.000	0.038	0.179
ROE	-3.279	75.99	-11.553	10.130	25.410
ASSETS	1,600,160	5,612,860	15,576	74,781	460,891
RET	-0.034	0.551	-0.312	0.045	0.305

Source: authors' calculations

Notes: Variable definitions: IVOL = annual idiosyncratic volatility. AQ = accruals quality measure given by the standard deviation of residuals from the Francis et al. (2005) regression model. AGE = is calculated as one plus the difference between current year and the firm's base date. BM = is the ratio between the book value of equity and the market value of equity. VCFO = is the variance of annual operating cash flow scaled by average total assets over the trailing five-year window. RET2 = squared annual buy-and-hold return. LEV = given by the ratio of long term debt on the book value of total assets. ROE = represents return on equity. ASSETS = total assets. RET = contemporaneous annual buy-and-hold return.

Our dependent variable is IVOL and we find a mean value of annual volatility 0.272. This value corresponds to a monthly volatility 0.023. In the case of the U.K. Angelidis and Tessaromatis (2008) report an average monthly IVOL 0.016, that exhibit the same order of magnitude as those reported here. We must emphasize that we use the direct estimation method based on the variance of the residuals of an asset pricing model, while Angelides and Tessaromatis (2008) follow the indirect estimation method developed by Campbell et al. (2001) and used by Goyal and Santa-Clara (2003), Wei and Zhang (2006) and Bali et al. (2005). Furthermore, our sampling period includes data from 1998 to 2015, while the sampling period of Angelides and Tessaromatis (2008) is from 1979 to 2003. In spite of not providing a specific empirical test, we suggest that our mean value could be higher because of the upward trend in IVOL documented in earlier studies. In the case of the U.S. stock markets, Rajgopal and Venkatachalam (2011), using the direct estimation method, report an average monthly IVOL 0.042.

As regards the main explanatory variable, AQ used to measure earnings quality, we find a mean value 0.064 which is slightly larger than 0.045 mean value reported by Rajgopal and Venkatachalam (2011) for the U.S. markets and for the period 1962-2001.

Table 2 contains the Pearson's correlation coefficients of the variables used to measure idiosyncratic volatility, earnings quality and other explanatory variables for idiosyncratic volatility. Correlation between AQ and IVOL is positive (0.321) and statistically significant at the 1% level. This result is consistent with the shares of firms with poor earnings quality exhibiting a high level of idiosyncratic volatility. As regards the correlations between IVOL and control variables, the larger correlation coefficients are relative to RET2 (0.474), ROE (-0.393) and RET (-0.378) and the signs of the estimated coefficients are the same as those

expected. Such results suggest that firms with increased disclosure of value-relevant information, low past earnings and low stock returns tend to exhibit higher levels of IVOL. The estimated coefficients for BM and LEV are opposite to that expected, but when we consider the whole set of explanatory variables in regression estimations only BM exhibits a statistically significant coefficient with a sign different from the expected.

Table 2: Correlations

	IVOL	AQ	AGE	BM	VCFO	RET2	LEV	ROE	ASSETS	RET
IVOL	1									
AQ	0.321***	1								
AGE	-0.263***	-0.279***	1							
BM	0.201***	-0.020	0.028***	1						
VCFO	0.038***	0.247***	-0.056***	-0.081***	1					
RET2	0.474***	0.176***	-0.172***	0.130***	0.024**	1				
LEV	-0.077***	-0.117***	0.112***	-0.035***	-0.019	-0.043***	1			
ROE	-0.393***	-0.264***	0.212***	-0.036***	-0.062***	-0.249***	0.087***	1		
ASSETS	-0.147***	-0.155***	0.211***	-0.087***	-0.049***	-0.099***	0.173***	0.115***	1	
RET	-0.378***	-0.104***	0.134***	-0.308***	-0.021**	-0.372***	0.009	0.284***	0.053***	1

Source: authors' calculations

Notes: ***, ** indicate significance at the 1 percent and 5 percent levels, respectively.

Variable definitions: IVOL = annual idiosyncratic volatility. AQ = accruals quality measure given by the standard deviation of residuals from the Francis et al. (2005) regression model. AGE = is calculated as one plus the difference between current year and the firm's base date. BM = is the ratio between the book value of equity and the market value of equity. VCFO = is the variance of annual operating cash flow scaled by average total assets over the trailing five-year window. RET2 = squared annual buy-and-hold return. LEV = given by the ratio of long term debt on the book value of total assets. ROE = represents return on equity. ASSETS = total assets. RET = contemporaneous annual buy-and-hold return.

A potential econometric problem is multicollinearity, which is related to high correlation between two or more independent variables. One of the procedures to assess the level of multicollinearity in a sample is based on the correlation matrix. Multicollinearity is a serious problem if the correlation between two explanatory variables is high (in excess of 0.8), Gujarati (2004). According to Table 2, correlation coefficients between explanatory variables are low, therefore we do not expect to have a multicollinearity problem in our sample.

5.2. REGRESSION OF IDIOSYNCRATIC VOLATILITY ON ACCRUALS QUALITY, INNATE AQ, DISCRETIONARY AQ AND CONTROL VARIABLES

In this section we develop a cross-sectional regression of idiosyncratic volatility on the three accrual-based measures of earnings quality after incorporating the control variables discussed above in this study. Specifically, we use as control variables firm age (AGE), book-to-market ratio (BM), variance of annual operating cash flows (VCFO), squared annual buy-and-hold return as a proxy for disclosure of value-relevant information (RET2), firm leverage (LEV), return on equity (ROE), natural logarithm of total assets (SIZE) and stock return (RET).

In regression estimations, we use panel data because it usually contains more degrees of freedom and more sample variability than cross-sectional data or time series, hence improving the efficiency of econometric estimates. In addition, it allows to control for

heterogeneity, controls the impact of omitted variables and reduces collinearity among variables, Gujarati (2004). In our estimations we use time fixed effects after running the Hausman test to decide between random or fixed effects.

Table 3 reports a positive association between AQ and IVOL and such association is statistically significant at the 1% level. When accruals quality is replaced by the innate component of AQ the estimated coefficient is positive and statistically significant at the 1% level and the same occurs when using the discretionary component of AQ. Even when both the innate and the discretionary component of AQ are included simultaneously in the regression the estimated coefficients are positive and statistically significant at the 1% level. However, the estimated coefficients of the innate component are higher than those of AQ and of the discretionary component. Such result is consistent with the higher impact of the uncertainty in the nature of the business on idiosyncratic volatility. These results support our research hypotheses from H1a to H1d and this finding is consistent with the noise view of idiosyncratic volatility suggesting that the poorest the information environment the higher the firm-specific volatility.

Table 3: Regression of idiosyncratic volatility on accruals quality (AQ), innate AQ, discretionary AQ and control variables

Dependent variable: Idiosyncratic volatility					
Independent variables	Pred. sign	EQ=AQ	EQ= INNATE AQ	EQ= DISC. AQ	EQ = INNATE AQ, DISC. AQ
INTERCEPT		0.368 *** (17.593)	0.175 *** (6.853)	0.427 *** (23.875)	0.189 *** (7.355)
AQ (t-1)	(+)	0.638 *** (10.283)			
INNATE AQ (t-1)	(+)		1.509 *** (13.305)		1.447 *** (12.664)
DISC. AQ (t-1)	(+)			0.362 *** (5.731)	0.257 *** (4.076)
AGE	(-)	-0.001 *** (-5.264)	-0.001 *** (-4.865)	-0.001 *** (-5.475)	-0.001 *** (-4.430)
BTM (t-1)	(-)	0.035 *** (8.766)	0.034 *** (9.178)	0.033 *** (8.772)	0.035 *** (9.453)
VCF (t-1)	(+)	0.005 (0.773)	-0.008 (-1.118)	0.013 ** (1.975)	-0.007 (-1.050)
RET2 (t-1)	(+)	0.117 *** (18.367)	0.109 *** (17.682)	0.115 *** (18.373)	0.108 *** (17.457)
LEV (t-1)	(+)	0.080 *** (3.067)	0.081 *** (3.366)	0.085 *** (3.494)	0.086 *** (3.568)
ROE (t-1)	(-)	-0.001 *** (-16.033)	0.001 *** (-14.020)	-0.001 *** (-17.474)	-0.001 *** (-14.065)
SIZE (t-1)	(-)	-0.018 *** (-10.627)	-0.008 *** (-4.205)	-0.021 *** (-13.028)	-0.009 *** (-4.772)
RET	(-)	-0.176 *** (-25.172)	-0.166 *** (-24.763)	-0.172 *** (-25.420)	-0.166 *** (-24.736)
Num.Observ.		6,079	5,854	5,854	5,854
Adj.R-squa.		0.381	0.391	0.376	0.392

Source: authors' calculations

Notes: ***, **, * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are presented in parentheses.

Variable definitions: the dependent variable is annual idiosyncratic volatility. AQ = accruals quality measure given by the standard deviation of residuals from the Francis et al. (2005) regression model. INNATE AQ = innate component of AQ. DISC. AQ = discretionary component of AQ. AGE = is calculated as one plus the

difference between current year and the firm's base date. BM = is the ratio between the book value of equity and the market value of equity. VCFO = is the variance of annual operating cash flow scaled by average total assets over the trailing five-year window. RET2 = squared annual buy-and-hold return. LEV = given by the ratio of long term debt on the book value of total assets. ROE = represents return on equity. SIZE = natural logarithm of total assets. RET = contemporaneous annual buy-and-hold return.

Regarding control variables, the estimated coefficients are all statistically significant at the 1% level, except for the volatility of cash-flows that is not statistically significant. The estimated coefficient for the book-to-market ratio is positive and opposite to that expected. In line with the finding of Pastor and Veronesi (2003), our results suggest that idiosyncratic volatility increases for younger firms because of their higher uncertainty about profitability. Regarding squared return used to capture the disclosure of value-relevant information we find a positive association as expected. Also, we find a positive association between leverage and IVOL, consistent with high levered firms being riskier. Increased firm performance, as measured by return on equity or stock return tends to reduce IVOL, as expected. Lastly, smaller firms tend to exhibit higher levels of IVOL. In short, we find that poor information environment, leverage and the intensity of information disclosure tend to increase IVOL, while more age, better performance and larger firms tend exhibit lower levels of IVOL.

5.3. REGRESSION OF IDIOSYNCRATIC VOLATILITY ON ACCRUALS QUALITY, INNATE AQ, DISCRETIONARY AQ, DISPERSION IN ANALYSTS' FORECASTS AND CONTROL VARIABLES

We aim at studying whether idiosyncratic volatility tends to increase for firms with poor information environments, consistent with the noise approach to idiosyncratic volatility. The regression estimated above shows a positive association between poor information environment, as proxied by accrual-based measures of earnings quality, and idiosyncratic return volatility. However, accrual-based measures may be noise indicators of earnings quality, thus, as a further development of our study we analyse the association between idiosyncratic volatility and accrual-based measure of earnings quality, but including the variable dispersion in analysts' forecast. The rationale behind our approach is that when managers have incentives to manipulate earnings they provide less expansive disclosure and this implies a higher degree of uncertainty in investors' beliefs and an increased dispersion in analysts' forecasts. We formulate our second hypothesis based on assumption that the association between idiosyncratic volatility and poor accrual-based measures is stronger for firms with a high dispersion in analysts' forecast.

We consider that firms with a higher dispersion in analysts' forecasts are likely to have poor information environments. This is so because when managers rely on accruals to communicate their private information they use all means to communicate the true firm performance to investors, thus reducing heterogeneity in analysts' beliefs about the performance of the firm.

To test the second hypothesis, we include in our regression a dummy variable, DISP, which is set to one for firms with annual analysts' forecast dispersion higher than 33rd percentile and set to zero for the remaining firms. For firms with DISP equal to one we expect to find a stronger positive association between poor accrual-based measures of earnings quality and IVOL. Specifically, we include in our regression a new term that results from multiplying the earnings quality measure by the dummy variable DISP. The estimated coefficient of this interaction term must be added to the estimated coefficient of the earnings quality measure for firms with DISP set to one. If our second hypothesis is true, the coefficient of this

interaction term should be positive and statistically significant. Our results show strong evidence that the estimated coefficient is positive and statistically significant. Such evidence holds when using as measures of earnings quality accruals quality, or the innate component of AQ, or the discretionary component of AQ or when including simultaneously both the innate and the discretionary components of AQ.

Table 4: Regression of idiosyncratic volatility on accruals quality (AQ), innate AQ, discretionary AQ, dispersion in analysts' forecasts and control variables

Dependent variable: Idiosyncratic volatility					
Independent variables	Pred. sign	EQ=AQ	EQ= INNATE AQ	EQ= DISC. AQ	EQ = INNATE AQ, DISC. AQ
INTERCEPT		0.305 *** (12.953)	0.192 *** (6.378)	0.358 *** (17.752)	0.191 *** (6.367)
AQ (t-1)	(+)	0.470 *** (5.792)			
INNATE AQ (t-1)	(+)		1.004 *** (6.361)		1.022 *** (6.499)
DISC. AQ (t-1)	(+)			0.263 *** (2.597)	0.269 *** (2.675)
DISP*AQ (t-1)	(+)	0.183 ** (2.111)			
DISP*INNATE AQ (t-1)	(+)		0.249 ** (2.451)		0.294 *** (2.901)
DISP*DISC AQ (t-1)	(+)			0.284 ** (1.987)	0.322 ** (2.263)
AGE	(-)	-0.001 ** (-1.962)	-0.001 ** (-2.116)	-0.001 * (-1.766)	-0.001 (-1.397)
BTM (t-1)	(-)	0.042 *** (8.791)	0.039 *** (8.583)	0.040 *** (8.651)	0.042 *** (9.106)
VCF (t-1)	(+)	0.009 (1.273)	0.003 (0.491)	0.013 ** (1.969)	0.004 (0.569)
RET2 (t-1)	(+)	0.102 *** (13.348)	0.099 *** (13.622)	0.104 *** (14.290)	0.097 *** (13.350)
LEV (t-1)	(+)	0.046 ** (2.063)	0.047 ** (2.264)	0.057 *** (2.720)	0.056 *** (2.700)
ROE (t-1)	(-)	0.001 *** (-10.575)	-0.001 *** (-9.497)	-0.001 *** (-11.728)	-0.001 *** (-9.493)
SIZE (t-1)	(-)	-0.015 *** (-8.247)	-0.009 *** (-4.368)	-0.017 *** (-10.263)	-0.009 *** (-4.635)
RET	(-)	-0.197 *** (-25.384)	-0.200 *** (-26.989)	-0.202 *** (-27.319)	-0.198 *** (-26.850)
Num.Observ.		3,652	3,583	3,583	3,583
Adj.R-squa.		0.429	0.449	0.446	0.455

Source: authors' calculations

Notes: ***, **, * indicate significance at the 1 percent, 5 percent and 10 percent levels, respectively. t-statistics are presented in parentheses.

Variable definitions: the dependent variable is annual idiosyncratic volatility. AQ = accruals quality measure given by the standard deviation of residuals from the Francis et al. (2005) regression model. INNATE AQ = innate component of AQ. DISC. AQ = discretionary component of AQ. DISP = dummy variable which is set to one for firms with annual analysts' forecast dispersion higher than 33rd percentile and set to zero otherwise. AGE = is calculated as one plus the difference between current year and the firm's base date. BM = is the ratio between the book value of equity and the market value of equity. VCFO = is the variance of annual operating cash flow scaled by average total assets over the trailing five-year window. RET2 = squared annual buy-and-hold return. LEV = given by the ratio of long term debt on the book value of total assets. ROE = represents return on equity. SIZE = natural logarithm of total assets. RET = contemporaneous annual buy-and-hold return.

Table 4 suggests that the positive association between accrual-based measures of earnings quality and IVOL is stronger for the subsample of firms with a high dispersion in analysts' forecast, because the coefficient of the interaction term is positive and statistically significant at the five percent level. This finding supports our second hypothesis and is consistent with the noise view of idiosyncratic volatility.

Regarding control variables, we find similar results to those described in the above regression, except for the five percent significance level of AGE and LEVERAGE.

5.4. TESTING THE NONLINEAR SPECIFICATION MODEL OF THE IVOL

In this section we develop further our first model. In order to test the likely nonlinear relation between IVOL and AQ we include, besides control variables, four dummy variables Q2, Q3, Q4 and Q5, identifying firms in accruals quality quintiles except for quintile one. We investigate if the estimated coefficients increase from the bottom quintile to the top quintile.

Table 5: Testing the nonlinear specification model

	Pred. sign	Panel Fixed Effects (OLS)			
		Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT		0.376	0.022	16.696	0.000
Q2 (t-1)	(+)	0.008	0.010	0.858	0.391
Q3 (t-1)	(+)	0.018	0.010	1.860	0.063
Q4 (t-1)	(+)	0.042	0.010	4.184	0.000
Q5 (t-1)	(+)	0.088	0.011	7.990	0.000
AGE	(-)	-0.001	0.000	-5.241	0.000
BM (t-1)	(-)	0.035	0.004	8.638	0.000
VCFO (t-1)	(+)	0.009	0.007	1.221	0.222
RET2 (t-1)	(+)	0.118	0.006	18.527	0.000
LEV (t-1)	(+)	0.083	0.026	3.144	0.002
ROE (t-1)	(-)	-0.001	0.000	-16.614	0.000
SIZE (t-1)	(-)	-0.018	0.002	-10.457	0.000
RET	(-)	-0.176	0.007	-25.074	0.000
Num.Observ.	6,079				
Adj.R-squa.	0.378				

Source: authors' calculations

Notes: Variable definitions: IVOL = annual idiosyncratic volatility. Qi = accruals dummy variable set to one for firms in quintile "i" and zero otherwise. AGE = is calculated as one plus the difference between current year and the firm's base date. BM = is the ratio between the book value of equity and the market value of equity. VCFO = is the variance of annual operating cash flow scaled by average total assets over the trailing five-year window. RET2 = squared annual buy-and-hold return. LEV = given by the ratio of long term debt on the book value of total assets. ROE = represents return on equity. SIZE = natural logarithm of total assets. RET = contemporaneous annual buy-and-hold return.

Table 5 reports that the estimated coefficients relative to the quintile dummies (Q2 to Q5) are all positive and statistically significant, except for Q2. Given that these estimated parameters reflect differences in the mean IVOL relative to quintile 1, which includes firms with better accruals quality, then all groups, except for Q2, exhibit higher mean IVOL than Q1. Moreover, the relationship between AQ and IVOL is nonlinear because we observe a

non-significant change in IVOL between the first and the second quintile while there is a substantial increase in the mean IVOL for the other quintiles, especially for the fourth and fifth quintiles.

Thus, the results are consistent with our third hypothesis that the positive association between poor AQ and IVOL is stronger for firms in higher level quintiles. Therefore, accruals quality is an effective indicator of poor earnings quality because firms with high values of AQ, which represent more volatile abnormal accruals, exhibit higher levels of IVOL. This means that high volatile abnormal accruals identify firms with poor public information which provides an informational advantage to informed investors. In addition, we suggest that this high level of AQ results from poor information environments, otherwise managers would disclose additional information in order to reduce the dispersion in beliefs among market participants.

6. CONCLUSIONS

In this research, we report evidence on a statistically significant positive association between poor information environments and firm-specific return volatility. Therefore, our study emphasizes that improving the quality of a firm's information environment reduces firm-specific return volatility. However, accruals may also be used to communicate private information. Such use of accruals is assumed to improve the quality of the firm's information environment. To overcome this issue we develop a method that consists in adding to accrual-based measures a new proxy that allows to separate firms by their prevalent motivation to use accruals. Using this method we arrive to the finding that combining accrual-based measures and the dispersion in analysts' forecasts, which we use as a proxy for the quality of the firm's information environment, results in a stronger association between the firm's information environment and idiosyncratic volatility. This finding contributes to the debate on whether firm-specific return volatility captures more firm-specific information being impounded in stock prices or essentially reflects noise. Our study supports the noise approach of idiosyncratic volatility, meaning that such volatility tends to reflect mainly noise.

This study also provides some results regarding the impact of control variables. Our tests show that, in the case of UK firms listed on the London Stock Exchange, smaller and younger firms, firms with increased information disclosure and more levered exhibit higher levels of firm-specific volatility, while a better performance tends to reduce such volatility.

Overall, our finding supporting the noise view of idiosyncratic volatility emphasizes the importance of improving the firms' information environment in order to reduce stock return volatility. Additionally, our results suggest that combining accrual-based measures of earnings quality with the dispersion in analysts' forecasts provides a better indicator of earnings quality. Those findings can be useful for a number of economic agents including investors in general, managers, auditors, regulators, policy makers and academics.

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