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Divergence of Opinion and Idiosyncratic Volatility

Diogo Silva[1]
Antonio Cerqueira[2]

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Abstract

Purpose – The main purpose of this study is to address the association between investors' divergence of opinion (DIVOP) and idiosyncratic volatility (IVOL).

Theoretical framework – A relevant association between DIVOP and IVOL is consistent with the literature on financial information disclosure (Lang and Lundholm, 1996; Rajgopal and Venkatachalam, 2011), future stock returns (Ang *et al.*, 2006; Diether *et al.*, 2009), mispricing (Miller, 1977; Aabo *et al.*, 2017), firm maturity (Berkman *et al.*, 2009; Fink *et al.*, 2010) and market imperfections (Berrada and Hugonnier, 2013).

Design/methodology/approach – We consider four proxies of DIVOP and four measures of IVOL and apply multivariate econometric tests to assess their association. Our models control for different effects such as first-order correlation (Huang, 2011) or firm maturity (Fink *et al.* 2010). We focus on UK firms listed on the London Stock Exchange, which is one of the largest stock markets in Europe.

Findings – We consistently found a positive and significant association between DIVOP and IVOL. We also observed that one-year lagged DIVOP is related to higher contemporaneous IVOL, even if we control for lagged IVOL. We show that even if our proxy for DIVOP captures divergence of opinion when liquidity is relatively high, we still find a positive and significant association between DIVOP and IVOL.

Practical & social implications of research – The main implications of the study is that DIVOP represents risk and that future research should address IVOL, its drivers and outcomes using the Fama and French (2015) five-factor model.

Originality/value – We provide empirical evidence that DIVOP is associated with IVOL, suggesting that DIVOP is a channel through which uncertainty generates IVOL, and its effect can persist throughout a whole year. We show that the association between DIVOP and IVOL is not the result of poor liquidity.

Keywords – divergence of opinion; idiosyncratic volatility; uncertainty.

1. *University of Porto, School of Economics and Management, Porto, Portugal*
2. *University of Porto, School of Economics and Management, Porto, Portugal*

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1 Introduction

The main purpose of this study is to assess the association between investors' divergence of opinion (DIVOP) and idiosyncratic volatility (IVOL). IVOL received much attention after the findings of Campbell, Lettau, Malkiel, and Xu (2001) and Ang, Hodrick, Xing, and Zhang (2006). However, after testing a large set of determinants of IVOL, Hou and Loh (2016) concluded that there is still a lot to be explained. IVOL is a pervasive macro variable (Guo & Savickas, 2006) that corresponds to more than 80% of total individual stock volatility (Ferreira & Laux, 2007). It is everywhere (Guo & Savickas, 2008; Ang, Hodrick, Xing, & Zhang, 2009) and predicts future stock returns (Ang *et al.*, 2006). It reflects anomalous dynamics because standard asset pricing models cannot explain it. Its existence defies the efficient market hypothesis and asset pricing models, which are the two main pillars of mainstream finance (Frankfurter & McGoun, 2002).

We focus on the relationship between DIVOP and IVOL for two reasons. There is increasing literature on the topic of DIVOP (see, for instance, Atmaz & Basak, 2018; Cujean & Hasler, 2017; Giannini, Irvine, & Shu, 2019). We believe the literature has undervalued the relevance of the relationship between DIVOP and IVOL. Ang *et al.* (2006) showed that the difference in alphas between the portfolio with the highest and lowest IVOL, in terms of future stock returns, goes from -1.19% to -0.39% when controlled for the dispersion in analysts' forecasts (a proxy for DIVOP). Still, this result has not received much attention. Most researchers addressing IVOL apply a portfolio analysis, which does not allow many controls to be accounted for at the same time. The R-squared of our multivariate tests actually range from 0.5 to 0.8.

A relevant association between DIVOP and IVOL is consistent with the literature on financial information disclosure, future stock returns, mispricing, firm maturity and market imperfections. Both lower financial reporting quality (Rajgopal & Venkatachalam, 2011) and firms' selective disclosure (Jiang, Xu, & Yao, 2009) are associated with IVOL. Rajgopal and Venkatachalam (2011) hypothesize that the explanation for the casual relationship could be the dispersion in analysts' forecasts, which is a proxy for DIVOP. When financial reporting quality is lower, analysts have to rely more on their private information, which increases the dispersion in analysts' forecasts. Analysts' beliefs are a reflection of investors' opinions (Nichols, 1989; Schipper, 1991).

The amount of firms' disclosure is also related with greater dispersion in analysts' forecasts (Lang & Lundholm, 1996), because it increases uncertainty and the weight that investors have to give to private valuations. We hypothesize that sources of uncertainty, such as limited information, increase divergences of opinion, which then translates into higher IVOL. Berrada and Hugonnier (2013) show that the impact of incomplete information over IVOL is much stronger for portfolios that present a large dispersion in analysts' forecasts, which is consistent with DIVOP being a channel through which uncertainty generates IVOL.

Both DIVOP and IVOL were found to be associated with lower future stock returns. Berkman, Dimitrov, Jain, Koch, and Tice (2009) applied five proxies for DIVOP and showed that stocks with higher DIVOP earn lower returns around earnings announcements. Likewise, IVOL predicts lower future stock returns in the US (Ang et al., 2006; Guo & Savickas, 2006), in the UK (Angelidis & Tessoromatis, 2008), in China (Gu, Kang, & Xu, 2018) and in many other stock markets (Ang *et al.*, 2009; Guo & Savickas, 2008).

Guo and Savickas (2008) obtained results that are consistent with IVOL signalling liquidity risk or DIVOP. They were not able to disentangle these two effects and suggest that this could be addressed in future research. Because one of our measures of DIVOP captures divergence of opinion when liquidity is relatively high, we test if there is a positive association between this measure of DIVOP and IVOL.

We compute IVOL as the average monthly volatility of the residuals of an asset pricing model. To make sure that the results do not depend on how we measure IVOL we use a total of four asset pricing models, namely the market model, the Fama and French (1993) three-factor model, the Carhart (1997) model and the Fama and French (2015) five-factor model. Important sources of uncertainty about future performance are growth options and investment opportunities (Bekaert, Hodrick, & Zhang, 2012; Guo & Savickas, 2008; Xu & Malkiel, 2003). Since we apply the Fama and French (2015) five-factor model, we are able to test whether the incorporation of systematic risk factors that capture investment and profitability affect the relationship between DIVOP and IVOL. Malagon, Moreno, and Rodríguez

(2015) showed that the IVOL puzzle dissipates if the Fama and French (2015) five-factor model is used.

We also consider different proxies for DIVOP. The first two are based on unexpected trading volume. Those proxies are based on the work of Garfinkel (2009), who concluded that they were the best proxies for DIVOP. In addition, we use two proxies for DIVOP that are based on the dispersion of analysts' forecasts. Those are the most common proxies for DIVOP used in the literature (Berkman *et al.*, 2009; Chatterjee, John, & Yan, 2012; Diether, Malloy, & Scherbina, 2002).

To develop the analysis, we focus on UK firms listed on the London Stock Exchange, which is one of the largest stock markets in Europe. This is important to avoid data snooping since most studies focus on the US. We consistently found a positive and significant association between DIVOP and IVOL. We also observed that one-year lagged DIVOP is related to higher contemporaneous IVOL, even when we control for lagged IVOL. We show that even if our proxy for DIVOP captures the divergence of opinion when liquidity is relatively high, we still find a positive and significant association between DIVOP and IVOL. In our tests, when we controlled for unobserved heterogeneity with both cross-sectional and time fixed effects, we found that the variable with the most explanatory power in our regression was contemporaneous DIVOP.

We contribute to the literature in several ways. Firstly, we provide empirical evidence that DIVOP is associated with IVOL. We deepen the understanding of this relationship since we consider different proxies for DIVOP and apply a multivariate analysis and our models control for different effects such as first-order correlation (Huang, Liu, Rhee, & Zhang, 2011) or firm maturity (Fink, Fink, Grullon, & Weston, 2010). We also show that there is some persistence in the impact of DIVOP over IVOL. The results are consistent with DIVOP being a channel through which uncertainty generates IVOL, and its effect can persist throughout a whole year. Secondly, we show that the association between DIVOP and IVOL is not the result of poor liquidity. This had been an issue raised by Guo and Savickas (2008). Thirdly, we document that the relationship between DIVOP and IVOL weakens when we compute IVOL using the Fama and French (2015) five-factor model, even though it remains statistically significant in most of the tests. Fourthly, we provide evidence for the UK.

The remainder of this article is organized as follows. Section 2 presents a brief literature review. Section 3 explains the methodological procedures. Section 4 shows the results of the empirical tests. Section 5 presents the conclusion.

2 Literature Review

Researchers have documented that there is a component of stock prices that cannot be explained by common asset pricing models (Morck, Yeung, & Yu, 2000; Roll, 1988). This is an anomalous fragment of stock price dynamics that is defined as the idiosyncratic component of stock prices. It is idiosyncratic because it is not explained by systematic risk factors. Hence, its dynamics are likely to be stock specific. Of course, the issue may be with how IVOL is measured. That is, the models may need to be improved in the sense that they may be lacking systematic risk factors. Morck *et al.* (2000) pointed out that the relevance of idiosyncratic risk has actually been surpassing systematic risk. Roll (1988) indicated that the explanatory power of asset pricing models over monthly stock returns corresponds to 35%. Frankfurter and McGoun (2002) mentioned that both asset pricing models and the efficient market hypothesis are the two main pillars of mainstream finance. The fact that idiosyncratic risk is priced represents a challenge for these two pillars.

There are two studies that have led to waves of papers addressing IVOL. Firstly, Campbell *et al.* (2001) showed that stock return volatility has been increasing since the sixties. More importantly, they pointed out that it is mainly due to the increase in IVOL. Many studies have addressed this trend (Brandt, Brav, Graham, & Kumar, 2009; Fink *et al.*, 2010; Gaspar & Massa, 2006; Rajgopal & Venatachalam, 2011; Xu & Malkiel, 2003). Secondly, Ang *et al.* (2006) found that stocks with higher IVOL present lower future stock returns. This finding is inconsistent with past literature (Merton, 1987) and is usually described as the IVOL puzzle. The puzzle is worldwide (Ang *et al.*, 2009; Guo & Savickas, 2008) and it has been documented that it is related with small caps (Angelidis & Tessaromatis, 2008), with past losers (Arena, Haggard, & Yan, 2008), earnings shocks and selective disclosure (Jiang, Xu, & Yao, 2009), arbitrage asymmetry (Stambaugh, Yu, & Yuan, 2015), other limits of arbitrage (Gu et al., 2018), the arrival of new public news (Shi, Liu, & Ho, 2016) or with macro finance factors (Aslanidis, Christiansen, Lambertides, & Savva, 2019).

Still, after testing a large set of determinants, Hou and Loh (2016) concluded that there is a lot to be explained.

We focus on the relationship between DIVOP and IVOL for two reasons. There has been increasing interest in the topic of DIVOP (see for instance Atmaz & Basak, 2018; Cujean & Hasler, 2017; Giannini *et al*., 2019). We believe the literature has undervalued the relevance of the relationship between DIVOP and IVOL. Firstly, Ang *et al.* 2006 found that the difference in alphas between the portfolio with the highest and lowest IVOL, in terms of future stock returns, was higher than minus one percent. In most of their robustness tests the difference was close to or even more than negative one percent. However, when they controlled for the dispersion in analysts' forecasts (a proxy for DIVOP), the difference in the alphas of high and low IVOL portfolios decreased to -0.39%. To put this value in perspective, consider Han and Lesmond (2011), who after applying the Carhart (1997) model and accounting for liquidity biases, found a difference in the alphas of high and low IVOL stocks of -0.51%. This value allowed them to conclude that IVOL has little pricing ability. Secondly, Ang *et al.* (2006) and most researchers addressing IVOL apply a portfolio analysis, which does not allow for many controls to be accounted for at the same time. Thirdly, in the multivariate approaches authors may have considered independent variables that correspond to alternative explanations of the IVOL puzzle that are correlated with DIVOP. Hou and Loh (2016) tested the ability of dispersion in analysts' forecasts to explain the IVOL puzzle along with other explanatory variables. The authors concluded that dispersion does not explain more than 6% of the puzzle. Some of the other explanatory variables were the bid-ask spread, which also captures DIVOP (Garfinkel, 2009), and one-month return reversals. Reversals is a proxy for mispricing, which is likely to be a consequence of DIVOP (Berkman *et al.*, 2009; Miller, 1977). Interestingly, bid-ask spread and one-month return reversals can explain up to 8% and 22% of the puzzle, respectively.

The relationship between DIVOP and IVOL can be explained through different topics, namely financial information disclosure, future stock returns, mispricing, firm maturity and market imperfections.

IVOL is correlated with firms' selective disclosure (Jiang, Xu, & Yao, 2009) and with lower financial reporting quality (Rajgopal & Venkatachalam, 2011). Rajgopal and Venkatachalam (2011) hypothesize that the explanation for the casual relationship between financial reporting quality and IVOL could be the dispersion in analysts' forecasts. They proposed that when the quality of financial information is lower, analysts have to rely more on their private information, thus leading to dispersion of their forecast. If investors follow different analysts, then there would be higher DIVOP among investors. We add that financial information with lower quality should affect investors' beliefs just as it affects dispersion among analysts. Analysts' beliefs actually provide a reflection of investors' opinions (Nichols, 1989; Schipper, 1991). Also, investors are likely to follow more than one analyst, so their opinion is not likely to depend on just one analyst. The amount of firms' disclosure has a negative association with dispersion in analysts' forecasts (Lang & Lundholm, 1996). Berrada and Hugonnier (2013) show that portfolios whose stocks are associated with greater dispersion in analysts' forecasts are associated with higher levels of IVOL and that the impact of incomplete information over IVOL is stronger for portfolios that present higher dispersion in analysts' forecasts.

Both DIVOP and IVOL were found to be associated with lower future stock returns. Miller (1977) proposed that the market would overweigh optimistic valuations if there are short-selling constraints. Scherbina (2001) showed that stock prices will mainly reflect the opinion of the most optimistic investors. Diether *et al.* (2002) concluded that firms for which there is higher DIVOP have lower future stock returns[1]. Berkman *et al.* (2009) focused on stock returns around earnings announcements and used five different proxies for DIVOP, incorporating stock market, earnings and analyst forecast-based proxies. They showed that stocks with higher DIVOP earn lower returns around earnings announcements. Chatterjee *et al.* (2012) found that the takeover premium increases with DIVOP and that a higher DIVOP is linked with a lower probability of a firm being a takeover target. Regarding IVOL, Ang *et al.* (2006) and Guo and Savickas (2006) showed that higher IVOL US stocks earn significantly lower future returns. The same happens in the UK (Angelidis & Tessaromatis, 2008), China (Gu *et al.*, 2018), in G7 countries (Guo & Savickas, 2008) and across 23 developed countries (Ang *et al.*, 2009).

The main explanation for the association between DIVOP and lower future stock returns is short-selling constraints (Miller, 1977), which generate arbitrage asymmetry. Some of the explanations for the IVOL puzzle are arbitrage asymmetry (Stambaugh *et al.*, 2015) and other arbitrage limits (Gu et al., 2018).

Stambaugh *et al.* (2015) show the IVOL puzzle holds for overpriced stocks but not for underpriced ones. The effect of overpriced stocks is stronger due to short-selling constraints and because there is greater arbitrage capital in long positions.

By showing that DIVOP is associated with lower future stock returns the literature suggests that DIVOP is associated with contemporaneous mispricing due to arbitrage limitations (Berkman *et al.*, 2009; Chatterjee *et al.*, 2012; Diether *et al.*, 2002; Miller, 1977). IVOL is also positively associated with mispricing and this relationship is stronger for overpriced stocks than for underpriced stocks (Aabo, Pantzalis, & Park, 2017).

DIVOP is lower for firms with higher maturity because these firms have a longer operating history and are likely to be at a more stable phase, thus reducing the uncertainty that investors face (Berkman *et al.*, 2009). Fink *et al.* (2010) argued that the findings of Campbell *et al.* (2001) that IVOL follows a positive trend were explained by new listings in the nineties of firms with low maturity, which increased uncertainty and thus idiosyncratic risk.

Overall, several dynamics point to the existence of a relationship between DIVOP and IVOL. Hence, the following hypothesis is tested:

Hypothesis 1: DIVOP is positively associated with IVOL.

DIVOP is caused by fast-learning investors that anticipate business cycle downturns (Cujean & Hasler, 2017). Bekaert *et al.* (2012) shows that IVOL is associated with a variance premium, which is a business cycle risk indicator. This hints at a non-simultaneous relationship between DIVOP and IVOL. Atmaz and Basak (2018) develop a model of belief dispersion and show that DIVOP generates excess stock return volatility. We hypothesise that IVOL reflects an iterative process of DIVOP. Uncertainty tends to boost DIVOP (Houge, Loughran, Suchanek, & Yan, 2001; Miller, 1977). One source of uncertainty can be poor disclosure (Lang & Lundholm, 1996). DIVOP will lead to stock return volatility (Atmaz & Basaz, 2018), which reflects higher idiosyncratic risk. The market will overweigh the most optimistic valuations (Miller, 1977; Berkman *et al.*, 2009), due to arbitrage limitations (Gu *et al.*, 2018; Stambaugh *et al.*, 2015). Later, lower stock returns will occur (Ang *et al.*, 2006; Berkman *et al.*, 2009). Thus, the following hypothesis is tested:

Hypothesis 2: Past DIVOP leads to higher IVOL.

Gaspar and Massa (2006) suggest that market competition is associated with IVOL because it increases uncertainty about the future performance of firms. Firm maturity is also related with IVOL because it increases uncertainty about future performance (Fink *et al.*, 2010). An important source of uncertainty about future performance is growth and investment opportunities. Xu and Malkiel (2003) point out that the focus on growth that dominated institutional investors' preferences during the late nineties may have redirected firms' preferences regarding investments. The search for growth through unique investments increased uncertainty, which may have then increased IVOL. Guo and Savickas (2008) indicate that firms' investment opportunities tend to increase stock prices, due to growth options, but also their volatility due to the uncertainty regarding which firms will benefit from the new opportunities. Bekaert *et al*. (2012) provide evidence consistent with growth opportunities being associated with IVOL and suggest that IVOL proxies for a systematic risk factor. Both Guo and Savickas (2008) and Ang *et al*. (2009) found that the spread between high and low IVOL differs between countries, which is consistent with IVOL proxying for a systematic risk.

Fama and French (2015) added two systematic risk factors to their well-known three-factor model (Fama & French, 1993). They added two additional factors that capture profitability and investment (Fama & French, 2015). Controlling for these spreads should limit the effect of investment and growth opportunities on uncertainty, which is the trigger that makes DIVOP generate IVOL. Malagon *et al.* (2015) found that the IVOL puzzle dissipates after computing IVOL using the Fama and French (2015) five-factor model. We thus test the following hypothesis:

Hypothesis 3: The association between DIVOP and IVOL weakens when the Fama and French five-factor model is used to compute IVOL.

Guo and Savickas (2008) obtain results that are consistent with IVOL signalling liquidity risk or DIVOP. They are not able to disentangle these two effects and suggest that this could be addressed in future research. Han and Lesmond (2011) show that one should account for liquidity when measuring IVOL. We use a proxy for DIVOP that is defined as abnormal trading volume (*ABVOL*). Following Garfinkel (2009), we compute it as firms' trading volume adjusted by market volume and firm's historical trading volume. This measure captures DIVOP in periods in which liquidity is expected to be high. When our measure points to high levels of DIVOP, this is not the outcome of low liquidity. On the contrary, it is consistent with high levels of liquidity. Proxying DIVOP using *ABVOL* allows us to test whether the relationship between DIVOP and IVOL holds after we account for liquidity risk.

Hypothesis 4: The relationship between DIVOP and IVOL is not the outcome of low liquidity.

3 Methodology

3.1 Data sources and sample

This study focuses on UK firms listed on the London Stock Exchange. Our primary source of data was Thomson Reuters Datastream. We retrieved data on analysts' forecasts from the Institutional Brokers Estimate System (I/B/E/S). Data on the time series of systematic risk factors and the risk-free return were taken from the Kenneth R. French website. We collected all the data available from 1998 until 2016. The UK government announced its withdrawal from the European Union in March of 2017. We excluded data from this date onwards. The withdrawal of the UK from the European Union had a persistent impact on the stock market performance of some firms (Ramiah, Pham, & Moosa, 2017), generating a structural break in these firms' time series. It also had a persistent effect on the interactions between the UK stock market and its European peers, having a substantial impact in terms of stock markets' co-volatility (Li, 2020).

Next, we applied a couple of criteria to adjust our sample. Firstly, we made sure to consider only firm-year observations compliant with International Financial Reporting Standards (IFRS). The purpose was to safeguard the comparability of the firms' accounting data. Since the mandatory adoption of IFRS started in 2005, the number of observations prior to this year is small because many firms were still applying national General Accepted Accounting Principles (GAAP) or we could not find information about the accounting standards that were being employed.

Secondly, we associated the firms with an industry category. To define each firm's industry we followed Fama and French (1997). Then we excluded from the analysis firms from the financial and utilities sectors. Those correspond to industry codes 31, 44, 45, 46, 47, and 48. Our initial extraction from the database contained 2999 firms. Our final dataset has 2132 firms.

Thirdly, all variables that we included in our models were windsorised at the first and last percentile. This kind of procedure has been applied in other studies that address idiosyncratic volatility, such as those of Brandt et al. (2009), Fink, Fink, and He (2012) or Irvine and Pontiff (2009).

3.2 Measurement of IVOL

We computed monthly IVOL as the standard deviation of the residuals from a regression of daily stock returns on systematic risk factors. The systematic risk factors considered depend on the asset pricing model used to define expected stock returns. Since the London Stock Exchange is the largest stock market in Europe, we used European systematic risk factors. The regressions were estimated for each year at the firm level. Annual IVOL equals the average monthly IVOL (see for instance Rajgopal & Venkatachalam, 2011). We used four measures of IVOL. Each one was tested against each different proxy for DIVOP.

The first measure of IVOL relies on the market model (*IV_MKT*). Specifically, for each year we ran the following regression:

$$(R_{i,t} - Rf_t) = B_0 + B_1.(Rmt - Rf_t) + e_{i,t}, \quad (1)$$

where for firm *i* and day *t*, *R* refers to realised stock return, *Rf* corresponds to the risk-free return and *Rm* is the return on the value-weighted market portfolio. For each month we computed the standard deviation of the residuals. Annual idiosyncratic equals the average monthly IVOL. For the second measure of IVOL we used the Fama and French (1993) three-factor model:

$$(R_{i,t} - Rf_t) = B_0 + B_1.(Rmt - Rf_t) + B_2.SMB_t + B_3.HML_t + e_{i,t}, \quad (2)$$

where for firm *i* and day *t*, *SMB* is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of large stocks and *HML* refers to the difference between the returns on diversified portfolios of high and low book-to-market stocks. Annual idiosyncratic volatility equals the average monthly IVOL. In this case we define it as *IV_FF3*. The third measure of IVOL is based on the Carhart (1997) model:

$$(R_{i,t} - Rf_t) = B_0 + B_1.(Rmt - Rf_t) + B_2.SMB_t + B_3.HML_t + B_4.MOM_t + e_{i,t}, \quad (3)$$

where for firm *i* and day *t*, *MOM* corresponds to the rate of return of a portfolio long on winner stocks and short on loser stocks. We define this measure of IVOL as *IV_MOM*. The fourth measure uses the residuals of the Fama and French (2015) five-factor model:

$$(R_{i,t} - Rf_t) = B_0 + B_1.(Rmt - Rf_t) + B_2.SMB_t + B_3.HML_t + B_4.RMW_t + B_5.CMA_t + e_{i,t} \quad (4)$$

where for firm *i* and day *t*, *RMW* refers to the difference between the returns on diversified portfolios of stocks with robust and weak profitability and *CMA* is the difference between the returns on diversified portfolios of stocks with conservative and aggressive investing stocks.

3.3 Proxies for DIVOP

We applied two different sets of proxies for DIVOP. The first set relies on unexpected trading volume. These measures are based on Garfinkel (2009). We used two measures of unexpected trading volume, which we defined as abnormal trading volume (*ABVOL*) and unexplained trading volume (*UNVOL*). *ABVOL* equals average monthly abnormal trading volume. Monthly abnormal trading volume is calculated as follows:

$$Monthly\_ABVOL_{i,t} = [(VOL_{i,t} - MKT\_VOL_t)] - [(FIRM\_AVG\_VOL_i - MKT\_AVG\_VOL_t)] \quad (5)$$

where for firm *i* and month *t*, *VOL* corresponds to shares traded divided by total shares outstanding, *MKT_VOL* equals total shares traded in the market divided by total shares outstanding in the market, *FIRM_AVG_VOL* refers to *VOL* averaged at the firm level and *MKT_AVG_VOL* is average market trading volume.

UNVOL equals average monthly unexplained trading volume. Monthly unexplained trading volume equals the residuals of the following regression:

$$VOL_{i,t} = B_0 + B_1.| positive\_R_{i,t} | + B_2.| negative\_R_{i,t} | + e_{i,t} \quad (6)$$

where for firm *i* and month *t*, *positive_R* corresponds to the logarithm of positive returns and *negative_R* refers to the logarithm of negative returns. Following Garfinkel (2009), we consider positive and negative returns separately because the relationship between trading volume and the absolute value of returns is different, depending on whether the returns are positive or negative (Karpoff, 1987). We exclude monthly observations when stock price has kept constant for three months. This allows better control for the impact of liquidity. Han and Lesmond (2011) show that liquidity biases are relevant when addressing IVOL.

The second set of proxies for DIVOP is based on dispersion in analysts' forecasts. Analysts' views provide a reflection of investors' opinions (Nichols, 1989; Schipper, 1991). Measuring DIVOP through dispersion in analysts' forecasts has been a common practice in the literature (Berkman *et al.*, 2009; Chatterjee *et al.*, 2012; Chen, Hong, & Stein, 2002; Diether *et al.*, 2002; Scherbina, 2001). We measure dispersion by the coefficient of variation of the forecasts of earnings per share (EPS), which is given by the absolute value of the ratio between the standard deviation of forecasts and the mean of absolute forecasts. The ratio is then multiplied by 100. We include in our tests two measures of dispersion. *DISP1* corresponds to the coefficient of variation of forecasts made one year ahead and *DISP2* is the coefficient of variation of forecasts made two years ahead.

3.4 Tests of the relationship between DIVOP and IVOL

Our multivariate tests aim at assessing the relationship between IVOL and DIVOP. We first study the contemporaneous association between the two. To ensure that the results are not driven by an omitted variable bias we include in our regressions several control variables. The following regression is estimated:

$$\begin{aligned} IVOL_{i,t} = {} & B_0 + B_1.ABVOL_{i,t} + B_2.RET_{i,t-1} + B_3.RET2_{i,t-1} + B_4.MTB_{i,t-1} \\ & + B_5.SIZE_{i,t-1} + B_6.LEV_{i,t-1} + B_7.ROE_{i,t-1} + B_8.AGE_{i,t-1} + B_9.IV_{i,t-1} + e_{i,t} \end{aligned} \quad (7)$$

$$\begin{aligned} IVOL_{i,t} = {} & B_0 + B_1.UNVOL_{i,t} + B_2.RET_{i,t-1} + B_3.RET2_{i,t-1} + B_4.MTB_{i,t-1} \\ & + B_5.SIZE_{i,t-1} + B_6.LEV_{i,t-1} + B_7.ROE_{i,t-1} + B_8.AGE_{i,t-1} + B_9.IV_{i,t-1} + e_{i,t} \end{aligned} \quad (8)$$

$$\begin{aligned} IVOL_{i,t} = {} & B_0 + B_1.DISP1_{i,t} + B_2.RET_{i,t-1} + B_3.RET2_{i,t-1} + B_4.MTB_{i,t-1} + B_5.SIZE_{i,t-1} \\ & + B_6.LEV_{i,t-1} + B_7.ROE_{i,t-1} + B_8.AGE_{i,t-1} + B_9.NANAL_{i,t-1} + B_{10}.ERRORS_{i,t-1} + B_{11}.IV_{i,t-1} + e_{i,t} \end{aligned} \quad (9)$$

$$\begin{aligned} IVOL_{i,t} = {} & B_0 + B_1.DISP2_{i,t} + B_2.RET_{i,t-1} + B_3.RET2_{i,t-1} + B_4.MTB_{i,t-1} + B_5.SIZE_{i,t} \\ & + B_6.LEV_{i,t-1} + B_7.ROE_{i,t-1} + B_8.AGE_{i,t-1} + B_9.NANAL_{i,t-1} + B_{10}.ERRORS_{i,t-1} + B_{11}.IV_{i,t-1} + e_{i,t} \end{aligned} \quad (10)$$

where for firm *i* and year *t*, *IVOL* refers to idiosyncratic volatility. We use four measures of IVOL in independent regressions. Those measures are *IV_MKT*, *IV_FF3*, *IV_MOM* and *IV_FF5*. These are based on the following asset pricing models: the market model, the Fama and French (1993) three-factor model, the Carhart (1997) model and the Fama and French (2015) five-factor model, respectively.

We consider four proxies for DIVOP. Each one of them refers to the first explanatory variable in each of the four regressions, namely *ABVOL, UNVOL*, *DISP1* and

DISP2. Each measure of IVOL is associated with each proxy for DIVOP.

RET is stock return performance. Ang *et al.* (2009) and Guo and Savickas (2008) show that for several developed countries, stocks with a higher IVOL present lower future stocks returns. Duffee (1995) pointed out that stock return performance is negatively associated with return volatility. Rajgopal and Venkatachalam (2011) found a negative association between stock return performance and IVOL in the US. Cerqueira and Pereira (2018) also observed a negative relationship in the UK. Thus, we expect to find a negative association between *RET* and IVOL.

RET2 corresponds to stock return performance squared. We follow Rajgopal and Venkatachalam (2011) and include it as an explanatory variable. The authors indicate that it is likely to capture the disclosure of value-relevant information. They found that it is positively associated with IVOL in the US. Cerqueira and Pereira (2018) observed the same outcome for the UK.

MTB refers to the market-to-book value of equity. By using this ratio instead of the book-to-market value of equity, we can directly proxy for growth opportunities. Accounting for growth opportunities is of the upmost importance, since the literature has pointed out many times that IVOL is linked with growth opportunities (Bekaert *et al*., 2012; Brown & Kapadia, 2007; Cao, Simin, & Zhao, 2008; Guo & Savickas, 2008; Xu & Malkiel, 2003). Hence, we expect a positive association between *MTB* and IVOL.

We include in our tests a control for *SIZE*. It equals the logarithm of the market value of equity. We expect a negative relationship between *SIZE* and IVOL. This relationship was found to be negative in the US (Pástor & Pietro, 2003), in Japan (Chang & Dong, 2006), in Australia (Liu & Di Iorio, 2016) and also in the UK (Cerqueira & Pereira, 2018).

LEV measures the leverage of firms and corresponds to long-term debt divided by total assets. Dennis and Strickland (2004) showed that IVOL is positively associated with leverage. Leverage enhances the negative association between IVOL and future stock returns (Ang *et al.*, 2009). More leveraged firms are more likely to be in financial distress and Chen, Chollete, and Ray (2010) show that firms in financial distress have explanatory power over the IVOL puzzle. Thus, we predict a positive association between *LEV* and IVOL.

We control firm performance by including *ROE* in our tests. It refers to return on equity and is computed as net income divided by the book value of equity. According to Huang, Liu, Rhee, and Zhang (2011), the IVOL puzzle is related to the return reversals of past winner stocks. Hence, we expect a negative association between *ROE* and IVOL.

AGE corresponds to the logarithm of the age of the firms. Uncertainty about future performance tends to be lower for mature firms because their operational history is longer and they are more likely to be at a stable stage (Berkman et al., 2009). As a result, IVOL is higher for younger firms due to greater uncertainty about future performance (Fink, Fink, Grullon, & Weston, 2010; Fink, Fink, & He, 2012; Pástor & Pietro, 2003). Therefore, we anticipate a negative association between *AGE* and IVOL.

When we use *DISP1* and *DISP2* to proxy for DIVOP we include in the regressions two additional control variables. *NANAL* refers to the number of analysts providing forecasts. We expect *NANAL* to be positively associated with IVOL, since there are more analysts following larger firms that disclose more information (Lang & Lundholm, 1996). *ERRORS* is the absolute difference of the mean of the analysts' forecasts and actual EPS, which is then divided by absolute actual EPS. We anticipate that past *ERRORS* should lead to higher *DIVOP*. *ERRORS* signals that the information environment is poorer, which is associated with higher IVOL (Cerqueira & Pereira, 2018).

Our last control variable is lagged IVOL. This is not a common control variable in this kind of analysis. Fu (2009) finds that the IVOL puzzle dissipates if exponential generalised autoregressive conditional heteroskedasticity (EGARCH) models are applied to estimate expected IVOL. Guo, Kassa, and Ferguson (2014) show that the findings presented by Fu (2009) bear some limitations, but they highlight an important issue, which is that there is significant and negative autocorrelation in monthly stock returns (see, for instance, Jegadeesh, 1990; Also, Huang, Liu, Rhee, & Zhang, 2009). They observe that the association found between IVOL and expected stock returns can be biased if the stock returns of the previous months are omitted from the estimations. This happens due to the return reversal of past winners. We expect that stocks with higher past IVOL will also present higher levels of IVOL in the future. A firm may have higher levels of IVOL in the past due to extreme performance and then keep showing high levels of IVOL due to the sweeping reversal of stock returns.

Our second hypothesis is that there is a positive association between past *DIVOP* and contemporaneous IVOL. To test this hypothesis, we also re-estimate the regressions presented above but we consider lagged *ABVOL* and lagged *UNVOL*. This allows us to test our second hypothesis. Since we are using annual data, a positive significant coefficient would indicate that the impact of DIVOP on IVOL is rather persistent, given it would imply that its effect can actually extend to the next year.

The regressions are firstly estimated with ordinary least squares. Since we use a panel data approach, we also apply cross-sectional and time fixed effects to account for unobserved heterogeneity. We chose to use fixed effects after applying the Hausman (1978) test. The null hypothesis of the test is that random effects is the preferred model. When we conducted the test we obtained a p-value of 0.000. This allowed us to reject the hypothesis that random effects was the preferred model.

4 Descriptive Statistics and Correlations

Table 1 displays the descriptive statistics for IVOL and DIVOP. Both the mean and the median of the different measures of IVOL are very similar (equal to 3 decimals). The mean of IVOL is 0.020. The magnitude of this value is in line with other studies for the UK (Angelidis & Tessaromatis, 2008; Cerqueira & Pereira, 2018), even though the time series of the samples of those studies are different. *ABVOL* has a mean (median) of 0.244 (0.298), which is lower than the 1.047 (-0.747) obtained for *UNVOL*. Both these proxies indicate DIVOP, but their computation is quite different. The mean (median) of *DISP1* corresponds to 18.516 (5.006) while *DISP2* has a mean (median) of 21.177 (6.839). This is consistent with forecasts made two years in advance having more uncertainty embedded, which translates into higher DIVOP.

Table 2 shows the correlations between the main variables under analysis. The correlation between the four measures of IVOL is very close to one. Both *UNVOL* and

Table 1
Descriptive statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
IV_MKT	0.020	0.019	0.062	0.005	0.008	1.295	5.081
IV_FF3	0.020	0.018	0.062	0.005	0.008	1.298	5.101
IV_MOM	0.020	0.018	0.062	0.005	0.008	1.301	5.119
IV_FF5	0.020	0.018	0.061	0.005	0.008	1.344	5.323
ABVOL	0.244	0.298	21.595	-21.764	5.466	0.152	6.650
UNVOL	1.047	-0.747	28.196	-5.946	5.954	2.286	9.258
DISP1	18.516	5.006	369.929	0.000	47.446	5.401	35.897
DISP2	21.177	6.839	373.105	0.000	49.246	5.175	33.306

Table 2
Pearson's correlations

	IV_MKT	IV_FF3	IV_MOM	IV_FF5	ABVOL	UNVOL	DISP1
IV_FF3	**1.000*****						
IV_MOM	1.000***	1.000***					
IV_FF5	0.994***	0.994***	0.994***				
ABVOL	0.302***	0.298***	0.297***	0.292***			
UNVOL	0.207***	0.202***	0.201***	0.186***	0.525***		
DISP1	0.307***	0.308***	0.309***	0.302***	0.015***	0.018***	
DISP2	0.358***	0.361***	0.361***	0.354***	0.032***	0.020***	0.516***

Note. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

ABVOL are not significantly correlated with *DISP1* and *DISP2*. All four proxies for DIVOP are positively and significantly correlated with the four measures of IVOL, which is consistent with the main hypothesis of this study. Nevertheless, the correlation between *UNVOL* and the measures of IVOL is lower when compared with the other proxies for DIVOP. *ABVOL* captures high levels of trading volume adjusted not only by the firms' history but also by the market. Thus, when our measure points to high levels of DIVOP, this is not the outcome of low liquidity. On the contrary, it is consistent with high levels of liquidity. We also apply a procedure to soften the impact of liquidity on the measurement of DIVOP through *UNVOL* but we cannot totally exclude this effect.

4.1 Multivariate Results

This section shows the multivariate tests. Table 3 displays the results of the regressions in which the proxy for DIVOP is *ABVOL*. Panel A (Table 3) shows the results of the regressions estimated by OLS while Panel B (Table 3) presents the regressions estimated with fixed effects. Regardless of the estimation method and how we measure IVOL, *ABVOL* is statistically significant at the 99% confidence level. In the OLS estimation, lagged IVOL is the most impactful variable, with a *t*-statistic that ranges from 112.106 to 113.822. *ABVOL* is the second most relevant variable. However, its *t*-statistic tends to be much lower, ranging from 16.423 to 17.611. This does not happen when we account for unobserved heterogeneity, since in the fixed effects estimation, *ABVOL* is the most important variable of the model. Its *t*-statistic increases to the 28.406-29.346 range, whereas the *t*-statistic of lagged IVOL decreases to between 21.472 and 22.676. The sign of the coefficients of the variables does not change with the measure of IVOL. Most of the control variables are statistically significant and the sign of their coefficients tends to be in line with our predictions and with past literature (Cerqueira & Pereira, 2018; Rajgopal & Venkatachalam, 2011). The main exception is *LEV*, which has a non-significant coefficient. In addition, *AGE* has a positive coefficient when a fixed effects estimation is applied. It may be the case that the firm-level fixed effects are capturing the same dynamics that *AGE* proxies for. For instance, firms listed for many years have similar levels of *AGE* throughout the whole sample. Increases in the number of years from 20 to 21, from 21 to 22 and from 23 to 24 are not relevant increases, especially since we compute *AGE* as the logarithm of the firms' age in years. Applying the logarithm is important because the impact of an increase in the age in years for a younger firm in terms of IVOL should be higher than the impact of an increase in the age in years for a mature firm because the decrease in terms of uncertainty is greater in the first case than in the latter. Overall, the results point out that there is a positive relationship between *ABVOL* and IVOL. Guo and Savickas (2008) were not able to conclude whether their results were consistent with an association between DIVOL and IVOL or between liquidity and IVOL. Note that *ABVOL* captures DIVOP when liquidity is high. Hence, the association between *ABVOL* and IVOL is not biased by liquidity issues. This supports our fourth hypothesis. Interestingly, the *t*-statistic of *ABVOL* is always the lowest when *IV_FF5* is used to measure IVOL. This is consistent with our third hypothesis, in that the relationship between DIVOP and IVOL is weaker when the Fama and French (2015) five-factor model is applied to compute IVOL.

Table 4 shows the results of the regressions in which the proxy for DIVOP is *UNVOL*. Panel A (Table 4) displays the estimations based on the OLS method while Panel B (Table 4) presents the estimations that use the fixed effects method. The results suggest a positive and significant association between *UNVOL* and IVOL. Again, when we do not include fixed effects the relevance of lagged IVOL is especially high, with it being the most important variable in the model, followed by *UNVOL*. When we control for unobserved heterogeneity, *UNVOL* becomes the most important variable in the model. Both the coefficient and *t*-statistic of *ABVOL* are higher than *UNVOL*. For instance, when IVOL is measured by *IV_FF5* and fixed effects are considered, their coefficient (*t*-statistic) corresponds to 0.040 (28.406) and 0.037 (19.398), respectively. Its *t*-statistic is the lowest when IVOL is measured by *IV_FF5,* independently of the estimation method. This is consistent with our third hypothesis that considering *RMA* and *CMW* in the asset pricing model used to estimate IVOL weakens the association between DIVOP and IVOL.

Table 5 presents the regression results in which the proxy for DIVOP is one-year lagged *ABVOL*. The aim of the analysis is to test our second hypothesis that past DIVOP has a positive association with IVOL. Our data are yearly and not monthly. Thus, we are addressing the persistence of the association between DIVOP and IVOL. If we use an OLS estimation we find a negative association between lagged *ABVOL* and IVOL. When we

Table 3
Regression results using abnormal trading volume (*ABVOL*) as the proxy for DIVOP

Panel A: OLS estimation								
	IV_MKT		**IV_FF3**		**IV_MOM**		**IV_FF5**	
	Coef.	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**
Intercept	1.100***	23.853	1.090***	23.778	1.088***	23.774	1.120***	24.216
ABVOL	0.023***	17.611	0.023***	17.450	0.023***	17.403	0.022***	16.423
RET (*t-1*)	-0.002***	-12.043	-0.002***	-12.308	-0.002***	-12.265	-0.001***	-11.092
RET2 (*t-1*)	0.000***	8.270	0.000***	8.379	0.000***	8.338	0.000***	7.413
MTB (*t-1*)	0.004***	2.499	0.004***	2.444	0.004***	2.411	0.004***	2.636
SIZE (*t-1*)	-0.030***	-8.819	-0.030***	-8.842	-0.030***	-8.869	-0.033***	-9.702
LEV (*t-1*)	0.031***	0.848	0.030***	0.841	0.030***	0.842	0.025***	0.703
ROE (*t-1*)	-0.035***	-4.646	-0.035***	-4.626	-0.035***	-4.638	-0.034***	-4.499
AGE (*t-1*)	-0.187***	-10.729	-0.186***	-10.739	-0.185***	-10.739	-0.185***	-10.708
IV_MKT (*t-1*)	76.664***	113.089						
IV_FF3 (*t-1*)			76.894***	113.754				
IV_MOM (*t-1*)					76.930***	113.822		
IV_FF5 (*t-1*)							76.644***	112.106
Adj. R^2	0.685		0.688		0.688		0.686	
N. obs.	8927		8927		8927		8927	
Panel B: Fixed effects estimation								
	IV_MKT		**IV_FF3**		**IV_MOM**		**IV_FF5**	
	Coef.	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**
Intercept	2.609***	19.328	2.595***	19.344	2.599***	19.406	2.654***	19.879
ABVOL	0.042***	29.346	0.041***	29.114	0.041***	29.058	0.040***	28.406
RET (*t-1*)	-0.001***	-6.249	-0.001***	-6.345	-0.001***	-6.336	-0.001***	-6.130
RET2 (*t-1*)	0.000***	5.421	0.000***	5.428	0.000***	5.425	0.000***	5.236
MTB (*t-1*)	0.002***	1.584	0.002***	1.559	0.002***	1.524	0.003***	1.697
SIZE (*t-1*)	-0.101***	-9.995	-0.101***	-9.985	-0.101***	-10.034	-0.105***	-10.426
LEV (*t-1*)	0.232***	4.255	0.231***	4.283	0.231***	4.280	0.220***	4.089
ROE (*t-1*)	-0.013***	-1.962	-0.013***	-2.040	-0.014***	-2.056	-0.012***	-1.845
AGE (*t-1*)	0.299***	5.162	0.295***	5.132	0.294***	5.120	0.288***	5.045
IV_MKT (*t-1*)	23.655***	22.626						
IV_FF3 (*t-1*)			23.766***	22.676				
IV_MOM (*t-1*)					23.705***	22.600		
IV_FF5 (*t-1*)							22.624***	21.472
Adj. R^2	0.814		0.815		0.816		0.815	
N. obs.	8927		8927		8927		8927	

Note. All coefficients were multiplied by 100 for expositional convenience. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

control for unobserved heterogeneity, we obtain a positive coefficient. We include lagged IVOL in all our models and to some extent this variable is already capturing lagged DIVOP, because, as demonstrated in Table 3 and Table 4, DIVOP and IVOL are positively associated. In untabulated results we find that if we exclude lagged IVOL we obtain a positive coefficient even if we use the OLS method. In addition, the positive coefficient of lagged *ABVOL* found for the fixed effects estimations becomes less significant with the level of refinement of the model. The *t*-statistic of the model in which the measure of IVOL is *IV_FF5* corresponds to 0.438, which compares with values between 1.635 and 1.938 for the other models. This supports the third hypothesis.

Table 4
Regression results using unexplained trading volume (*UNVOL*) as the proxy for DIVOP

	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
Panel A: OLS estimation								
	Coef.	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**
Intercept	1.895***	30.348	1.867***	30.126	1.859***	30.052	1.892***	30.090
UNVOL	0.034***	21.636	0.033***	21.376	0.033***	21.301	0.032***	20.499
RET (*t-1*)	-0.002***	-10.802	-0.002***	-11.121	-0.002***	-11.044	-0.001***	-9.565
RET2 (*t-1*)	0.000***	7.917	0.000***	8.061	0.000***	7.987	0.000***	6.831
MTB (*t-1*)	0.007***	3.798	0.007***	3.743	0.006***	3.705	0.007***	4.021
SIZE (*t-1*)	-0.076***	-17.826	-0.075***	-17.709	-0.075***	-17.685	-0.078***	-18.239
LEV (*t-1*)	0.003***	0.067	0.001***	0.026	0.001***	0.033	-0.008***	-0.194
ROE (*t-1*)	-0.049***	-5.187	-0.048***	-5.175	-0.048***	-5.190	-0.048***	-5.138
AGE (*t-1*)	-0.203***	-10.609	-0.201***	-10.620	-0.200***	-10.612	-0.198***	-10.492
IV_MKT (*t-1*)	68.543***	77.770						
IV_FF3 (*t-1*)			68.953***	78.539				
IV_MOM (*t-1*)					69.050***	78.641		
IV_FF5 (*t-1*)							68.608***	76.746
Adj. R^2	0.696		0.700		0.700		0.697	
N. obs.	6080		6080		6080		6080	
Panel B: Fixed effects estimation								
	IV_MKT		**IV_FF3**		**IV_MOM**		**IV_FF5**	
	Coef.	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**
Intercept	2.986***	17.757	2.949***	17.632	2.952***	17.670	3.029***	18.201
UNVOL	0.040***	20.617	0.039***	20.309	0.039***	20.222	0.037***	19.398
RET (*t-1*)	-0.001***	-7.077	-0.001***	-7.201	-0.001***	-7.143	-0.001***	-6.752
RET2 (*t-1*)	0.000***	6.148	0.000***	6.176	0.000***	6.121	0.000***	5.783
MTB (*t-1*)	0.006***	3.339	0.006***	3.275	0.005***	3.222	0.006***	3.408
SIZE (*t-1*)	-0.121***	-10.050	-0.118***	-9.929	-0.119***	-9.974	-0.124***	-10.463
LEV (*t-1*)	0.372***	5.153	0.373***	5.204	0.374***	5.232	0.355***	4.989
ROE (*t-1*)	-0.040***	-4.704	-0.041***	-4.792	-0.041***	-4.791	-0.039***	-4.617
AGE (*t-1*)	0.194***	3.010	0.191***	2.982	0.190***	2.985	0.188***	2.962
IV_MKT (*t-1*)	22.912***	17.255						
IV_FF3 (*t-1*)			23.183***	17.398				
IV_MOM (*t-1*)					23.111***	17.318		
IV_FF5 (*t-1*)							21.688***	16.147
Adj. R^2	0.833		0.834		0.834		0.833	
N. obs.	6080		6080		6080		6080	

Note. All coefficients were multiplied by 100 for expositional convenience. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

Table 6 shows the regression results in which the proxy for DIVOP is lagged *UNVOL*. We find that there is a positive and statistically significant association between lagged *UNVOL* and IVOL, independently of the estimation method. This is consistent with the second hypothesis that there is some persistence in the impact of DIVOP over IVOL. Besides, the coefficient of lagged *UNVOL* is the lowest, when IVOL is measured by *IV_FF5*. In fact, lagged *UNVOL* is only not statistically significant at the 99% confidence level when we apply the Fama and

Table 5
Regression results using lagged abnormal trading volume (*ABVOL*$_{t-1}$) as the proxy for DIVOP

Panel A: OLS estimation								
	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	0.932***	19.773	0.926***	19.788	0.925***	19.806	0.950***	20.213
ABVOL (*t-1*)	-0.011***	-8.267	-0.011***	-8.408	-0.011***	-8.466	-0.013***	-9.663
RET (*t-1*)	-0.001***	-11.131	-0.002***	-11.449	-0.001***	-11.421	-0.001***	-10.326
RET2 (*t-1*)	0.000***	6.950	0.000***	7.122	0.000***	7.101	0.000***	6.265
MTB (*t-1*)	0.002***	1.477	0.002***	1.453	0.002***	1.432	0.003***	1.618
SIZE (*t-1*)	-0.022***	-6.239	-0.022***	-6.311	-0.022***	-6.354	-0.024***	-7.090
LEV (*t-1*)	0.003***	0.071	0.004***	0.121	0.005***	0.134	0.001***	0.041
ROE (*t-1*)	-0.017***	-2.223	-0.017***	-2.265	-0.017***	-2.307	-0.017***	-2.217
AGE (*t-1*)	-0.197***	-11.215	-0.196***	-11.255	-0.195***	-11.254	-0.194***	-11.241
IV_MKT (*t-1*)	79.703***	115.124						
IV_FF3 (*t-1*)			79.903***	115.868				
IV_MOM (*t-1*)					79.937***	115.989		
IV_FF5 (*t-1*)							79.761***	114.915
Adj. R^2	0.671		0.675		0.676		0.676	
N. obs.	9154		9154		9154		9154	

Panel B: Fixed effects estimation								
	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	1.886***	12.714	1.879***	12.764	1.883***	12.824	1.914***	13.103
ABVOL (*t-1*)	0.003***	1.938	0.003***	1.700	0.003***	1.635	0.001***	0.438
RET (*t-1*)	-0.001***	-7.190	-0.001***	-7.302	-0.001***	-7.291	-0.001***	-7.108
RET2 (*t-1*)	0.000***	5.753	0.000***	5.789	0.000***	5.788	0.000***	5.619
MTB (*t-1*)	0.000***	-0.208	0.000***	-0.185	0.000***	-0.202	0.000***	-0.034
SIZE (*t-1*)	-0.061***	-5.621	-0.061***	-5.648	-0.062***	-5.704	-0.064***	-5.984
LEV (*t-1*)	0.157***	2.744	0.161***	2.841	0.162***	2.862	0.152***	2.708
ROE (*t-1*)	-0.005***	-0.663	-0.006***	-0.783	-0.006***	-0.825	-0.005***	-0.651
AGE (*t-1*)	0.397***	6.337	0.394***	6.342	0.393***	6.351	0.393***	6.394
IV_MKT (*t-1*)	30.954***	25.865						
IV_FF3 (*t-1*)			31.067***	25.989				
IV_MOM (*t-1*)					31.017***	25.948		
IV_FF5 (*t-1*)							30.388***	25.419
Adj. R^2	0.782		0.784		0.784		0.785	
N. obs.	9154		9154		9154		9154	

Note. All coefficients were multiplied by 100 for expositional convenience. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

French (2015) five-factor model to compute IVOL. This is in line with our third hypothesis that adding *CMA* and *RMW* to the asset pricing model used to estimate IVOL weakens the association between DIVOP and IVOL, since those variables can capture uncertainty driven by growth and investment opportunities. The relationship between growth and investment opportunities and IVOL is well documented in the literature (Bekaert *et al.*, 2012; Guo & Savickas, 2008; Xu & Malkiel, 2003).

Table 7 displays the regression results in which the proxy for DIVOP is *DISP1*. In this case we consider two additional control variables, namely *NANAL* and *ERRORS*. As expected, *ERRORS* is negatively associated with higher IVOL. *NANAL* has a different coefficient

Table 6
Regression results using lagged unexplained trading volume ($UNVOL_{t-1}$) as the proxy for DIVOP

	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
Panel A: OLS estimation								
	Coef.	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**
Intercept	1.290***	19.377	1.270***	19.256	1.267***	19.243	1.283***	19.219
UNVOL (*t-1*)	0.019***	12.541	0.018***	12.314	0.018***	12.243	0.016***	11.061
RET (*t-1*)	-0.001***	-7.626	-0.001***	-7.987	-0.001***	-7.933	-0.001***	-6.606
RET2 (*t-1*)	0.000***	3.814	0.000***	4.003	0.000***	3.956	0.000***	2.903
MTB (*t-1*)	0.003***	1.901	0.003***	1.892	0.003***	1.874	0.004***	2.141
SIZE (*t-1*)	-0.041***	-9.141	-0.040***	-9.095	-0.040***	-9.106	-0.042***	-9.531
LEV (*t-1*)	-0.057***	-1.288	-0.055***	-1.273	-0.055***	-1.264	-0.060***	-1.394
ROE (*t-1*)	-0.029***	-3.108	-0.029***	-3.133	-0.029***	-3.165	-0.029***	-3.204
AGE (*t-1*)	-0.171***	-8.690	-0.169***	-8.711	-0.169***	-8.707	-0.164***	-8.489
IV_MKT (*t-1*)	72.742***	79.085						
IV_FF3 (*t-1*)			73.151***	79.915				
IV_MOM (*t-1*)					73.211***	80.030		
IV_FF5 (*t-1*)							73.062***	78.697
Adj. R^2	0.670		0.674		0.675		0.672	
N. obs.	6179		6179		6179		6179	
Panel B: Fixed effects estimation								
	IV_MKT		**IV_FF3**		**IV_MOM**		**IV_FF5**	
	Coef.	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**	**Coef.**	***t*-stat**
Intercept	1.889***	10.080	1.861***	10.009	1.868***	10.064	1.888***	10.248
UNVOL (*t-1*)	0.009***	4.331	0.008***	4.098	0.008***	4.028	0.005**	2.542
RET (*t-1*)	-0.001***	-6.767	-0.001***	-6.947	-0.001***	-6.922	-0.001***	-6.719
RET2 (*t-1*)	0.000***	5.185	0.000***	5.285	0.000***	5.260	0.000***	5.071
MTB (*t-1*)	0.002***	0.954	0.002***	0.951	0.002***	0.926	0.002***	1.071
SIZE (*t-1*)	-0.052***	-3.998	-0.051***	-3.938	-0.051***	-3.994	-0.054***	-4.235
LEV (*t-1*)	0.339***	4.554	0.342***	4.628	0.343***	4.653	0.333***	4.565
ROE (*t-1*)	-0.009***	-0.977	-0.009***	-1.054	-0.010***	-1.079	-0.008***	-0.968
AGE (*t-1*)	0.298***	4.285	0.300***	4.356	0.300***	4.365	0.315***	4.627
IV_MKT (*t-1*)	28.267***	18.687						
IV_FF3 (*t-1*)			28.445***	18.830				
IV_MOM (*t-1*)					28.355***	18.766		
IV_FF5 (*t-1*)							27.334***	18.086
Adj. R^2	0.806		0.807		0.808		0.809	
N. obs.	6179		6179		6179		6179	

Note. All coefficients were multiplied by 100 for expositional convenience. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

depending on the estimation method. Firms with more analysts tend to be the largest ones. There is less uncertainty for those. Therefore, a negative coefficient would be more intuitive. We get a positive coefficient when we apply fixed effects. We must point out that for many firms in the sample the number of analysts is rather stable. Hence, firms' fixed effects may be already capturing rather stable characteristics such as *NANAL*. The *t*-statistics for *NANAL*

Table 7

Regression results using dispersion in analysts' forecasts made one year in advance (*DISP1*) as the proxy for DIVOP

Panel A: OLS estimation								
	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	0.346***	3.635	0.341***	3.641	0.340***	3.646	0.437***	4.687
DISP1	0.001***	5.150	0.001***	5.145	0.001***	5.172	0.001***	4.731
RET (*t-1*)	-0.001***	-5.304	-0.001***	-5.603	-0.001***	-5.510	-0.001***	-3.584
RET2 (*t-1*)	0.000***	1.339	0.000***	1.463	0.000***	1.435	0.000***	0.259
MTB (*t-1*)	-0.001***	-0.483	-0.001***	-0.482	-0.001***	-0.490	0.000***	-0.178
SIZE (*t-1*)	0.027***	3.451	0.026***	3.417	0.026***	3.400	0.019***	2.543
LEV (*t-1*)	0.109***	2.149	0.108***	2.148	0.107***	2.151	0.097***	1.953
ROE (*t-1*)	0.016***	1.016	0.014***	0.941	0.014***	0.910	0.013***	0.836
AGE (*t-1*)	-0.059***	-2.740	-0.058***	-2.737	-0.058***	-2.743	-0.061***	-2.893
NANAL (*t-1*)	-0.010***	-4.897	-0.010***	-4.932	-0.010***	-4.925	-0.009***	-4.566
ERRORS (*t-1*)	0.006***	2.136	0.006***	2.174	0.006***	2.199	0.006***	2.301
IV_MKT (*t-1*)	70.726***	56.034						
IV_FF3 (*t-1*)			71.262***	56.761				
IV_MOM (*t-1*)					71.355***	56.848		
IV_FF5 (*t-1*)							69.841***	53.930
Adj. R^2	0.499		0.506		0.507		0.483	
N. obs.	4197		4197		4197		4197	
Panel B: Fixed effects estimation								
	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	1.039***	4.564	1.010***	4.475	1.014***	4.506	1.139***	5.143
DISP1	0.001***	2.613	0.001***	2.606	0.001***	2.632	0.000***	1.706
RET (*t-1*)	-0.001***	-4.971	-0.001***	-5.066	-0.001***	-5.033	-0.001***	-4.633
RET2 (*t-1*)	0.000***	2.742	0.000***	2.775	0.000***	2.785	0.000***	2.454
MTB (*t-1*)	-0.002***	-0.847	-0.002***	-0.817	-0.002***	-0.845	-0.001***	-0.732
SIZE (*t-1*)	0.005***	0.334	0.006***	0.389	0.006***	0.360	-0.002***	-0.158
LEV (*t-1*)	0.610***	7.187	0.611***	7.279	0.610***	7.288	0.564***	6.887
ROE (*t-1*)	0.027***	2.219	0.025***	2.071	0.025***	2.057	0.027***	2.267
AGE (*t-1*)	0.080***	1.084	0.081***	1.110	0.080***	1.100	0.071***	0.995
NANAL (*t-1*)	0.004***	1.692	0.005***	1.802	0.005***	1.836	0.006***	2.538
ERRORS (*t-1*)	0.010***	2.724	0.010***	2.786	0.010***	2.822	0.009***	2.740
IV_MKT (*t-1*)	29.089***	16.698						
IV_FF3 (*t-1*)			29.495***	16.935				
IV_MOM (*t-1*)					29.515***	16.944		
IV_FF5 (*t-1*)							27.221***	15.471
Adj. R^2	0.783		0.783		0.783		0.779	
N. obs.	4197		4197		4197		4197	

Note. All coefficients were multiplied by 100 for expositional convenience. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

are indeed much smaller in the fixed effects estimations. Overall, we found a significant and positive relationship between *DISP1* and IVOL in all eight regressions that we estimated (four measures of IVOL and two estimation methods). This is in line with previous studies, but those have mainly focused on forecasts one month ahead (Hou and Loh, 2016). The *t*-statistic of *DISP1* is smaller when we measure IVOL through *IV_FF5*, which is consistent with the previous results disclosed and supports our third hypothesis. Still, in this case, the relationship remains statistically relevant at the 99% confidence level.

Table 8 shows the regression results in which the proxy for DIVOP is *DISP2*. We found a positive and significant association between *DISP2* and IVOL. The *t*-statistics of *DISP2* tend to be higher than for *DISP1*. Forecasts made two years in advance have more uncertainty embedded. Thus, *DISP2* can better gauge the link between DIVOP and IVOL. For instance, we know that when firms disclose lower amounts of information, the dispersion in analysts' forecasts tends to be higher (Lang & Lundholm, 1996). In addition, lower financial reporting quality is associated with more IVOL (Cerqueira & Pereira, 2018; Rajgopal & Venkatachalam, 2011). Both less disclosure and lower financial reporting quality generate higher uncertainty. Thus, more statistically significant coefficients for *DISP2* are understandable. The *t*-statistic of *DISP2* is the lowest when the measure of IVOL is *IV_FFF5*. This is a dynamic that we found in all of our tests, even though the descriptive statistics of *IV_FF5* are very similar to the other measures of IVOL. In this case, the Fama and French (2015) method does not eliminate the statistical significance of the association between DIVOP and IVOL, but it does weaken it.

4.2 Additional Tests

Autocorrelation

We do not find evidence of autocorrelation in our models. The Durbin-Watson statistics of the models range from 1.72 to 2.05. Their median is 1.93. There is no autocorrelation if we exclude lagged IVOL from the regressions. In this case we still find a positive and even more significant association between DIVOP and IVOL and also between one-year lagged DIVOP and IVOL. When we exclude lagged IVOL and estimate the regressions using period seemingly unrelated regressions (SUR) to deal with autocorrelation, our conclusions are the same, except that instead of finding a negative association between lagged *ABVOL* and IVOL, we actually find a positive one, consistent with the second hypothesis.

Heteroskedasticity

We considered heteroskedasticity in the cross-section and in the time series separately. We re-estimated all regressions using the generalised least squares (GLS) method with cross-sectional weights. We found that the results were not biased by heteroskedasticity since they did not change significantly. The same conclusions were also obtained when we re-estimated the models using GLS with period weights.

Measurement errors and additional control variables

In the baseline tests we considered four measures of IVOL, four proxies of DIVOP and two different estimation methods. In total we disclosed 48 tests, because we wanted to assess if our conclusions depended on the way we measured the main variables of the model, namely DIVOP and IVOL. In additional tests we also reframed how we measured the control variables and the proxies for DIVOP that are based on dispersion in analysts' forecasts. We also incorporated additional control variables that figured in other research related with idiosyncratic volatility. Instead of measuring *SIZE* by the natural logarithm of market value of equity, it was computed as the natural logarithm of total assets. We replaced *ROE* with *ROA* (net income divided by total assets). *LEV* was calculated as total debt divided by total assets as an alternative to long-term debt divided by total assets. Instead of using the logarithm of the firms' age to compute *AGE*, we simply used the absolute value of the firms' age in years. To calculate *ERRORS*, actual EPS was compared with the median of forecasts and not the mean. *NANAL* became the logarithm of the number of analysts following the firms instead of the absolute value. We revised the proxies for *DIVOP* based on analysts' forecasts. *DISP1* and *DISP2* were alternatively computed as the standard deviation of analysts' forecasts divided by the absolute median of forecasts, instead of the mean. We included variables capturing operating cash flows and their volatility (Rajgopal & Venkatachalam, 2011), as well as a variable capturing if the group is diversified in terms of operational activities (Aabo *et al.*, 2017). Overall, changing the measurement of the variables and adding

Table 8

Regression results using dispersion in analysts' forecasts made two years in advance (*DISP2*) as the proxy for DIVOP

Panel A: OLS estimation								
	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	0.346***	4.364	0.341***	4.388	0.340***	4.395	0.437***	5.415
DISP2	0.001***	7.598	0.001***	7.645	0.001***	7.673	0.001***	7.140
RET (*t-1*)	-0.001***	-4.896	-0.001***	-5.179	-0.001***	-5.083	-0.001***	-3.207
RET2 (*t-1*)	0.000***	0.914	0.000***	1.030	0.000***	0.996	0.000***	-0.154
MTB (*t-1*)	-0.001***	-0.523	-0.001***	-0.523	-0.001***	-0.528	0.000***	-0.211
SIZE (*t-1*)	0.027***	2.960	0.026***	2.910	0.026***	2.890	0.019***	2.046
LEV (*t-1*)	0.109***	1.958	0.108***	1.960	0.107***	1.961	0.097***	1.757
ROE (*t-1*)	0.016***	1.207	0.014***	1.134	0.014***	1.103	0.013***	1.020
AGE (*t-1*)	-0.059***	-2.804	-0.058***	-2.809	-0.058***	-2.812	-0.061***	-2.949
NANAL (*t-1*)	-0.010***	-4.612	-0.010***	-4.636	-0.010***	-4.629	-0.009***	-4.312
ERRORS (*t-1*)	0.006***	2.902	0.006***	2.951	0.006***	2.972	0.006***	3.175
IV_MKT (*t-1*)	70.726***	52.614						
IV_FF3 (*t-1*)			71.262***	53.290				
IV_MOM (*t-1*)					71.355***	53.389		
IV_FF5 (*t-1*)							69.841***	50.514
Adj. R^2	0.495		0.503		0.503		0.478	
N. obs.	4124		4124		4124		4124	
Panel B: Fixed effects estimation								
	IV_MKT		IV_FF3		IV_MOM		IV_FF5	
	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Intercept	1.039***	4.224	1.010***	4.118	1.014***	4.160	1.139***	4.862
DISP2	0.001***	4.022	0.001***	4.112	0.001***	4.106	0.000***	3.347
RET (*t-1*)	-0.001***	-4.682	-0.001***	-4.769	-0.001***	-4.733	-0.001***	-4.296
RET2 (*t-1*)	0.000***	2.301	0.000***	2.325	0.000***	2.333	0.000***	2.024
MTB (*t-1*)	-0.002***	-0.987	-0.002***	-0.961	-0.002***	-0.993	-0.001***	-0.870
SIZE (*t-1*)	0.005***	0.660	0.006***	0.739	0.006***	0.699	-0.002***	0.096
LEV (*t-1*)	0.610***	7.338	0.611***	7.421	0.610***	7.429	0.564***	6.978
ROE (*t-1*)	0.027***	2.464	0.025***	2.324	0.025***	2.313	0.027***	2.517
AGE (*t-1*)	0.080***	0.963	0.081***	0.974	0.080***	0.961	0.071***	0.867
NANAL (*t-1*)	0.004***	1.958	0.005***	2.069	0.005***	2.112	0.006***	2.920
ERRORS (*t-1*)	0.010***	3.251	0.010***	3.330	0.010***	3.363	0.009***	3.398
IV_MKT (*t-1*)	29.089***	16.327						
IV_FF3 (*t-1*)			29.495***	16.574				
IV_MOM (*t-1*)					29.515***	16.588		
IV_FF5 (*t-1*)							27.221***	15.080
Adj. R^2	0.784		0.785		0.785		0.781	
N. obs.	4124		4124		4124		4124	

Note. All coefficients were multiplied by 100 for expositional convenience. *,**,*** represent statistical significance with a confidence level of 90%, 95% and 99%, respectively.

other control variables did not meaningfully affect the results, allowing us to conclude that our findings are robust.

Outliers

All the variables were windsorised at the first and last percentile. However, we still assessed if outliers were biasing the results since the measures of IVOL and DIVOP, especially the ones based on unexpected trading volume, can be rather erratic. We reproduced the analysis by applying the robust least squares method. There were no changes in our conclusions when we did this.

New listings and exits

Fink *et al.* (2010) pointed out that the increase in IVOL in the nineties was explained by new listings of younger firms. To safeguard against our results being driven by new listings or exits we reproduced the tests but considered only firms with at least ten observations. This did not significantly affect the results.

5 Conclusion

We documented a positive and significant association between DIVOP and IVOL. This was expected given how both variables relate with other ones, such as information (Berrada & Hugonnier, 2013; Rajgopal & Venkatachalam, 2011), future stock returns (Ang *et al.*, 2006; Berkman *et al*. 2009) or firms' maturity (Berkman *et al.*, 2009; Fink *et al.*, 2010). We used proxies for DIVOP based on unexpected trading volume and dispersion in analysts' forecasts. We also computed IVOL using four different asset pricing models. The conclusions hold across all measures of both DIVOP and IVOL. We controlled for stock return performance, size, performance, leverage, growth opportunities, maturity and past IVOL. In additional tests we showed that our findings are not biased by autocorrelation, heteroskedasticity, measurement errors or by omitted variables, outliers or new listings and exits. The finding that DIVOP is significantly associated with IVOL is in line with Andersen et al. (2005), who suggest that DIVOP may be a price risk factor.

The results also suggest that lagged DIVOP leads to higher IVOL, which is consistent with the findings of Atmaz and Basak (2018), who argue that DIVOP generates excess stock return volatility.

We also showed that the relationship between DIVOP and IVOL exists independently of the level of liquidity. This had been an issue raised by Guo and Savickas (2008). In addition, we found that, across all tests, when the Fama and French (2015) five-factor model is used to compute IVOL, the association between DIVOP and IVOL weakens, but remains statistically significant in most of the tests. Controlling for investment and profitability appears to limit the impact of uncertainty regarding future performance associated with investment and growth opportunities (Bekaert *et al.*, 2012; Guo & Savickas, 2008; Xu & Malkiel, 2003). However, the descriptive statistics of IVOL computed using the different asset pricing models are very similar. Our findings are to some extent consistent with those of Malagon *et al.* (2015), who found that the IVOL puzzle dissipates if the Fama and French (2015) five-factor model is used to compute IVOL. An implication of this study is that future research should address IVOL, its drivers and outcomes using the Fama and French (2015) five-factor model.

Notes

[1] Chen and Jiambalvo (2004) showed the results obtained by Diether *et al.* (2002) can be explained by post-earnings announcement drift. Doukas, Kim, & Pantzalis (2006) also showed the results do not hold if the approach suggested by Barron, Kim, Lim, & Stevens (1998) is applied.

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Authors:
1. Diogo Silva, PhD candidate, University of Porto, Portugal.
Email: dsilva@fep.up.pt
2. Antonio Cerqueira, PhD, University of Porto, Portugal.
Email: acerqueira.pt@gmail.com

Authors' Contributions:

1st author: Definition of research problem; Development of hypotheses or research questions (empirical studies); Development of theoretical propositions (theoretical work); Definition of methodological procedures; Data Collection; Literature review; Statistical analysis; Analysis and interpretation of data; Manuscript writing.

2nd author: Definition of research problem; Definition of methodological procedures; Literature review; Statistical analysis; Analysis and interpretation of data; Critical revision of the manuscript;