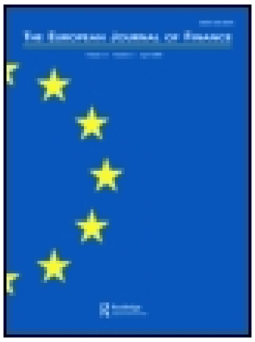

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Expected profitability, the 52-week high and the idiosyncratic volatility puzzle

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ABSTRACT
We investigate the joint ability of fundamental-based and market-based news to explain the anomalous underperformance of stocks with high idiosyncratic volatility (high IVOL). An out-of-sample prediction of future profitability is adopted as a proxy for fundamental–based news while market-based news is represented by the 52-week high price ratio. A sample of UK stocks over the period January 1996 to December 2017 is analysed. The empirical results indicate that both the fundamental-based projected profitability and the 52-week high price ratio are important in explaining the IVOL anomaly. In contrast, individually, neither variable fully accounts for the anomaly. This relation is more pronounced following a period of high sentiment and during an upmarket. Further results suggest that underreaction lies at the heart of this explanation.

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1. Introduction

The idiosyncractic volatility (IVOL) puzzle (Ang et al. 2006) suggests that low-volatility stocks outperform high-volatility stocks and has become a prominent anomaly across international markets (Ang et al. 2009). Widespread interest in this puzzle has led to a range of potential explanations for it, but the literature lacks a consensus. This puzzle is a concerning one as it runs counter to existing asset pricing models. Moreover, extensions to standard asset pricing models, such as CAPM or ICAPM, are unable to explain the puzzle, which has led to alternative risk-based explanations being advanced (Barinov 2018; Chen and Petkova 2012). Alternative competing explanations include those based around (irrational) investor behaviour and notably include the desire for extreme upside returns (referred to as lottery stocks; Mitton and Vorkink 2007; Kumar 2009; Han and Kumar 2013) and the role of investor sentiment (Bali, Cakici, and Whitelaw 2011; Fong and Toh 2014; Hou and Loh 2016). A recent promising line of enquiry advances the view of left-tail momentum linked to underreaction and limits to arbitrage (Hirshleifer and Teoh 2003; Atilgan et al. 2020). Under this view, investors, for cognitive and market friction reasons, underreact to value relevant information and a continuation trend appears in the market. In this paper, we seek to consider both fundamental and market (behavioural) factors. One difficulty in the existing literature is separately identifying such factors. We address this by explicitly modelling expected profitability as the fundamental factor, and using a price-related variable, which we identify as capturing the behavioural aspect if it is not subsumed by the fundamental factor.

In considering existing research, while empirical observations regarding the inability of well-known risk factors to explain anomalies may direct attention toward a behavioural view, these behavioural explanations would have a better theoretical grounding if, in turn, they are linked to firm fundamentals. Further, much of

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the current analysis is devoted to examining idiosyncratic risk, and related anomalies, conditioned on realised market information as opposed to expected information.[1] We believe both of these issues are under-researched.[2]

There are several reasons why expectations regarding firm fundamentals can provide useful information for the idiosyncratic risk anomaly. This includes research that highlights that IVOL payoffs are highly persistent (e.g. Ang et al. 2006), which can arise from slow investor response to news about expected fundamentals. Further, anomalies can be linked to firm performance. For example, Liu and Zhang (2017) link the momentum effect and future growth, while George, Hwang, and Li (2018) link predictive power of the 52-week high price ratio for returns to future profit. Similar links are noted by Byun, Goh, and Kim (2020) and Kyosev et al. (2020). This work suggests a connection between the IVOL effect and future profitability. Moreover, Riedl, Sun, and Wang (2021) show that investors misprice the value in expected profit conditioned on sentiment behaviour, where, for example, investors understate the persistence of losses in a high sentiment period.

The view within this line of enquiry is that informational inefficiency by investors arises from biased expectations and responses to firm fundamentals. The model of Hong and Stein (1999) assumes that momentum and reversals are generated by the interaction between two trader types. Specifically, 'newswatchers' who process and forecast firm fundamentals and 'momentum traders' who condition on past prices changes. Assuming information diffuses gradually, price momentum is initiated by the slow response of newswatchers and extended by momentum traders. This heterogeneous information processing motivates considering both projected fundamental and market based information. That is, the inclusion of expectations about firm profitability and market information should inform future stock return behaviour.

Previous research almost exclusively employs realised profitability as a proxy for expected profitability. However, both pricing theory and recent empirical evidence suggest a positive relation between future returns and expected profit. Using different estimation procedures, Clubb and Naffi (2007), Lin and Lin (2019) and Detzel, Schaberl, and Strauss (2019) show that expected profitability contributes significantly to the prediction of future returns and contains information beyond that embedded in the past distribution. Therefore, the role of expected fundamentals in the pricing equation should be considered.

The above suggest that expected profitability, as fundamental news, could be informative in regard of the IVOL effect. Equally, information from market prices can capture behavioural aspects. However, considering the combined role of these factors is an open and under-researched question. This paper seeks to fill this gap and contribute by investigating the ability of expected profit and the 52-week high price ratio to explain the IVOL effect and thus, capturing both a fundamental and behaviour signal. We do this by employing the Fama and French (1993) portfolio sorting technique and build factors that mimic the payoffs of expected profit and the 52-week high ratio.

To measure expected profit we follow the approach of Fama and French (2006) and Hou and van Dijk (2019) and employ a cross-section regression to model firm profitability using a set of selected variables. Our results show that both expected profitability (EROA) and the 52-week high price ratio (PH52) predict future realised returns for UK stocks, where average returns increase with PH52 and EROA. The creation of a zero-cost portfolio that goes long on the highest decile of EROA (PH52) and short on the lowest decile generates a positive return. Consistent with the main conjecture in this study, we report both the existence of the IVOL effect and that EROA and PH52 are negatively associated with IVOL. Moreover, this negative association explains a substantial part of the IVOL effect. This is further supported by Fama-MacBeth cross-section regressions that also confirm the ability of EROA and PH52 to predict the future returns and subsume the IVOL effect. This result is confirmed when accounting for a set of competing returns predictors.

Therefore, our results support the view that both fundamental- (expected profitability) and market-based (52-week high) news hold information for future returns and the poor performance of stocks with high idiosyncratic volatility. These findings are robust to alternatives proxies for profitability, while further analysis identifies that the IVOL effect is stronger with high sentiment. Hence, the IVOL effect is more likely to arise from investor mis-valuation of news. Overall, we argue that the IVOL puzzle arises from investor underreaction to persistent poor performance across both fundamental and market news.

It is hoped that our results improve understanding of market behaviour and asset pricing and are informative for investors. By their very nature, pricing anomalies represent potential deviations from our standard models of pricing in finance. These models represent our best understanding of investor behaviour in the market.

Consequently, in the presence of these anomalies, two potential reasons exist, that the market is inefficient and future trends in financial asset returns are predictable, or that our knowledge, and therefore our models, of market behaviour are flawed. Therefore, understanding the nature of pricing anomalies is primary to the develop a better model of investor behaviour, which then allows various market agents to make more efficient decisions. Our results, hopefully, add to this understanding.

2. Literature review

In explaining the idiosyncratic volatility (IVOL) anomaly, we argue that both expected profitability (fundamental) and price (behavioural) based information are important. Moreover, we believe that the link between the two is under-researched as most existing work focusses on realised information. There are several reasons why expectations of firm fundamentals can provide information for the IVOL anomaly. First, payoffs associated with IVOL anomalies are highly persistent. Notably, work reports persistent returns predictability from IVOL over the subsequent 12 months (see, for example, Ang et al. 2006). Such a pattern is not explained by overreaction, for which we would observe reversals, while underreaction is likely to have shorter persistency. Rather, this arises from slow investor response to expected fundamental news. Where an investor underreacts to expected fundamentals, they would then be surprised by the realised information, and a continuation trend in returns will be observed.

Second, recent studies link IVOL-related anomalies (typically, referred to as lottery-like stocks and includes the max-price effect of Bali, Cakici, and Whitelaw 2011) to expected profit. This includes Liu and Zhang (2017) who link momentum with future growth, while George, Hwang, and Li (2018) note the ability of the 52-week high price ratio to predict future returns could arise from its ability to predict future profit. Byun, Goh, and Kim (2020) find a similar result, while Kyosev et al. (2020) link accounting quality and future profit that enables the former to predict future market returns. These empirical relations suggest that the IVOL effect links with future profitability and, consequently, may be the channel through which IVOL predicts future returns. Where the IVOL effect is concentrated in stocks with a low 52-week high ratio, extreme past losses and lower accounting quality, it can capture an expected downturn in profitability and returns. Riedl, Sun, and Wang (2021) show that investors misprice the value embedded in expected profit conditioned on sentiment. In a period of high sentiment, investors understate the persistence of losses and overstate profit persistence and vice versa.

Third, behavioural theories link pricing anomalies to investors over- or/and under-reaction. Generally, this is triggered by biased expectations and responses to firm fundamentals. In the theory of Hong and Stein (1999), momentum and reversal is generated by the interaction of 'newswatchers', who monitor firm fundamentals and 'momentum traders', who condition only on past price changes. Assuming information diffuses gradually, excessive price momentum is generated by the slow response of newswatchers and the subsequent action by momentum traders. Thus, we believe the inclusion of expectations about firm profitability as well as market information will be informative about future stock returns.

Fourth, past research almost exclusively employs realised profitability as a proxy for expected profitability.[3] However, both pricing theory and recent empirical evidence suggest a positive relation between future returns and expected profitability. Clubb and Naffi (2007), Lin and Lin (2019) and Detzel, Schaberl, and Strauss (2019) show that expected profitability contributes significantly to the prediction of future returns and possesses useful information beyond that embedded in the past distribution.

The above points suggest that both fundamental and behavioural factors can explain the IVOL anomaly. However, this remains an open and under-researched question. Therefore, we aim to address this gap by investigating the ability of expected profit and the 52 week high price ratio to account for the IVOL effect. In addition, we argue that such variables themselves will be able to predict future returns.

In linking profitability to stock returns, several papers identify a profitability premium (see, Novy-Marx 2013; Nichol and Dowing 2014; Ball et al. 2016; Fama and French 2015, 2016; Hou, Xue, and Zhang 2015; Wahal 2019; Hanauer and Huber 2019). While the q-factor model (Hou, Xue, and Zhang 2015) can be used to explain this relation, a growing body of work relates the premium to investor mispricing. Min et al. (2018) note that the variation in the profitability premium is negatively related to the business cycle. Wang and Zhu (2017), employing short-selling activity, find the profitability premia is attributed to investor sentiment and the absence of arbitrage trading. Wang and Yu (2013) link the profitability premium to investor under-reaction attributed to limited attention bias.

Several studies report an empirical relation between expected profitability and IVOL-related anomalies. George, Hwang, and Li (2018) suggest the predictive power of the 52-week high ratio arises from its ability to predict future profitability as well as returns, whereby stocks with high IVOL trade at a price further from its 52-week price (Byun, Goh, and Kim 2020). Empirical evidence also notes that the IVOL effect is a sentimentally driven mispricing (Stambaugh, Yu, and Yuan 2015) with the IVOL effect stronger for stock with a low 52-week high ratio and after a period of high sentiment.[4]

In looking to summarise previous work, there is a general view that mispricing can arise from both market information (e.g. Byun, Goh, and Kim 2020) and fundamental news (e.g. Kyosev et al. 2020). In seeking to provide a synthesis to this work, we argue that the IVOL predictive power for returns is explained, partly by expected firm profitability and partly by investor sentiment based on past information anchoring. This results in a slow adjustment process and will generate momentum in returns in the direction of future profit. Previous work, for example, Battman et al., Chen et al. (2014), Hong and Wu (2016) and Zhu et al. (2020) all note the importance of considering both fundamental- and market-based information, which is consistent with the model of Hong and Stein (1999). While this paper is most closely related to Malagon, Moreno, and Rodríguez (2015) and George, Hwang, and Li (2018), it is distinguished in several aspects. Notably, we estimate profitability using a fundamental-based model in contrast to using past profit as a proxy for future profitability. We also test the separate and joint effects of expected profitability and the 52-week high ratio. While George, Hwang, and Li (2018) argue that the 52-week high ratio might affect profitability, but estimating an explicit model for expected profitability, we can consider whether the 52-week high ratio is subsumed in that, or has a separate influence upon returns.

3. Data and methodology

The sample includes all common stocks traded on the main market at the London stock exchange over the period from January 1996 to December 2017. To avoid survivorship bias, currently listed and unlisted firms are included in the sample. Following the past literature, financial firms are excluded, as are stocks with a price less than £3 or traded for less than 150 days over the last year (the formation period) and stocks with no available earnings data or negative book equity. Market price related data are from the Datastream database. Accounting variables are obtained from the Wordscope database in Datastream. The pricing factors and the risk-free rate data are obtained from Gregory, Tharyan, and Christidis (2013).[5]

3.1. Idiosyncratic volatility

Our main variable of interest is idiosyncratic volatility, for which we follow Ang et al. (2006). For each month we estimate the following Carhart (1997) pricing model:

$$R_{it} - rf_t = \alpha_i + \beta_m * \ (R_{mt} - rf_t) + \beta_{smb} * \mathrm{SMB}t + \beta_{hml} * \mathrm{HML}_t + \beta_{umd} * \mathrm{UMD}_t + \varepsilon_{it} \tag{1}$$

where R_{it} is the return of stock i on day t, R_{mt} is the market return on day t, rf_t is the risk-free rate, SMB_t is the small minus big size factor, HML_t is the high minus low value factor, UMD_t is the winner minus loser momentum factor and $?_{\mathrm{it}}$ is the unexplained return component, while α_i, β_m, $\beta_{smb,}$ β_{hml}, and β_{umd} are the estimated parameters. After estimating Equation (1), idiosyncratic volatility is calculated as the standard deviation of the residuals.

3.2. Price to 52-week high (PH52)

Evidence on the anchoring bias in financial markets states that investors pay limited attention to value-relevant news and maintain old reference points in their valuation. George and Hwang (2004) claim that the continuation pattern associated with a 52-week high strategy is a manifestation of anchoring bias. Li and Yu (2012), George, Hwang, and Li (2015) and Hur and Singh (2019) all suggest the 52-week high ratio is a proxy for limited investor attention. The ratio is calculated as:

$$PH52 = P_{it}/52 - \text{week high price}, \tag{2}$$

where P_{it} is the current closing price for stock *i* and the denominator is the highest price recorded during the past 52 weeks. According to anchoring bias and previous empirical evidence, stocks with a closing price far from the past 52-week high price are likely to underperform in subsequent periods. Therefore, the returns of the IVOL strategy are expected to be stronger for stocks with a price far from the past 52-week high.

3.3. Expected profitability

As noted above, previous work utilises realised profitability, however, we argue that a model for expected profitability is preferred. An argument in favour of using realised profitability is that it is known to be highly persistent (see, Fama and French 2006, and reference therein). However, profitability is also mean reverting (Fama and French 2000). Furthermore, recent work identifies a range of factors that can predict profitability. For example, dividend paying firms are expected to be more profitable than non-dividend payers (Fama and French 1999), while Hou and Robinson (2006) and Hou and van Dijk (2019) find that Tobin's q-theory predicts future profitability, with Richardson, Teoh, and Wysocki (2004) and Papanastasopoulos (2020) doing likewise for accruals. Dickinson (2011) and Vorst and Yohn (2018) also suggest that firm life cycle information helps forecast firm profitability. As such, recent empirical work applies a cross-section approach to predict next period's earnings (see, for example, Lee, So, and Wang 2011; Harris and Wang 2019; Hou and van Dijk 2019). While there is no consensus on the nature and number of earnings predictors, a parsimonious set is preferred. Therefore, subsequent year profitability is estimated, month by month, as follows:[6]

$$\begin{aligned}\mathrm{ROA}_{i,t} + 1 = {} & \alpha_0 + \alpha_1 \mathrm{ROA}i, t + \alpha_2 \mathrm{Negi}, t + \alpha_3 \mathrm{TQ}i, t + \alpha_4 Di, t + \alpha_5 D_{i,t}/B_{i,t} + \alpha_6 \mathrm{PACC}_{i,t} + \alpha_7 \mathrm{DLife}i, t \\ & + \alpha_8 \mathrm{Revi}, t + \varepsilon_{i,t+1}\end{aligned} \tag{3}$$

where ROA is the return on asset of firm i in year t and defined as the ratio of net income to lagged book assets, $\mathrm{Neg}_{\mathrm{i,t}}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise, $TQ_{i,t}$ is Tobin's q (market equity plus total liability scaled by book assets), $\mathrm{D}_{\mathrm{i.t}}$ is a dummy variable that equals 1 for dividend payers and 0 otherwise, $D_{i,t}/B_{i,t}$ is the ratio of dividend payment to book value equity, $\mathrm{PACC}_{i,t}$ is the percent accruals and is measured as the change in operating assets scaled by the absolute value of net income, DLife is a dummy variable according to the stage of the firm lifecycle (following Dickinson 2011) and Rev is the difference between ROA in the last year and average of ROA over the past 3 years.

After estimating Equation (3), the parameters are applied to the last available observations of the variables to forecast subsequent profitability from which we generate an out-of-sample expected profitability series. To ensure availability of the information, the accounting observations from the year ending at least 6 months previous are considered in estimation. For example, to estimate the next year's profitability in June 1997, the observations collected at the end of December of 1996 are required.

To ensure robustness of our analysis against alternative profitability definitions, we also consider profitability measured by the return on book equity, operating profit to book equity, and cash-based operating profit to book assets. The cash-based operating profit is calculated as the difference between operating profit and total accruals.

3.4. Control variables

To further ensure robust results and to account for the effect of other return predictors, we include a control set of return predictors widely documented in the literature. These variables are detailed in the appendix and include a range of both fundamental, accounting and price related factors, including market beta, price ratios, price trends and asset growth.

3.5. Methodology

To examine the IVOL puzzle in the UK stock market, we first consider the performance of investment strategies based on expected profitability (EROA) and the 52-week high (PH52) using a single portfolio sort. Each month stocks are sorted in ascending order into deciles according to EROA or PH52. The performance of these portfolios is evaluated by examining their raw returns over the next 3 and 12 months. In addition, the risk-adjusted performance is evaluated by the alpha from the 4-factor model of Carhart (1997).

The performance of the IVOL effect is then evaluated conditional on EROA and PH52. Here, a triple-sort portfolio analysis is performed to consider the performance of the IVOL strategy according to the level of EROA and PH52. Each month stocks are sorted into two portfolios based on the EROA or PH52. Then, four portfolios are built by intersecting the two EROA-based portfolios with the two PH52-based portfolios. Within each of these four portfolios, stocks are re-sorted into three portfolios according to the IVOL level. This therefore, produces twelve portfolios. A zero-cost strategy that is long in the high IVOL portfolio and short in the low IVOL portfolio is built within each level of EROA and PH52. Similar to the single sort analysis, performance is evaluated by the raw returns and the alpha of the 4-factor Carhart (1997) model. To consider the association between these three trading strategies in a multivariate setting, the well-known Fama and MacBeth cross-section regression is performed.

3.6. Pricing factor construction

In addition to the cross-section analysis, the relation between EROA, PH52 and IVOL is investigated in a time series setting. Here, two pricing factors are built to mimic the movement of payoffs to an investment strategy based on the EROA and PH52.

To achieve this, we follow the procedure established in Fama and French (1993). Each June, stocks are sorted into 3 groups based on EROA and PH52 using breakpoints for the bottom 30% (low), middle 40%, and upper 30% (high) of ranked stocks. Based on market capitalisation (size), stocks are also sorted into a big (upper 30%) and a small (bottom 70%) group. For the EROA factor, six portfolios are generated by intersecting the EROA-based groups with the two size groups and the EROA factor is calculated as the difference between the average returns of the two high and the two low EROA portfolios. To build the PH52 factor, eighteen portfolios are built by intersecting the three PH52 groups with the three EROA groups and the two size groups. The PH52 factor is defined as the difference between the average returns of the six high and the six low PH52 portfolios. Thus, the PH52 portfolios are neutral to information included in size and EROA. The size factor is defined as the difference between the average returns of the nine small and the nine big size portfolios. The size factor is rebalanced on an annual basis.

4. Empirical results

4.1. Descriptive statistics, correlation and profitability prediction

Table 1 presents the summary statistics for our data in Panel A. To provide a brief discussion, the average of idiosyncratic volatility is 2.68%, which comparable with the reported figures for the US (see, for example, Byun, Goh, and Kim 2020). On average, fundamental and market performance of UK stocks is poor, average ROA and monthly returns are −1% and −0.1%, respectively. The studies of Konstantinidi, Kraft, and Pope (2016), Cotter and McGeever (2018) and Artikis and Papanastasopoulos (2019) confirm this poor performance for the UK market. The table shows that, to some extent, moments of the fitted profitability (EROA) distribution resemble that of realised profitability (ROAt + 1). UK stocks are less liquid than US stocks with 16% of trading days having zero returns while US stock have a lower percentage of zero return days (see, Fong, Holden, and Trzcinka 2017).

Table 1, Panel B presents the average coefficients for the profitability regression together with their time-series t-statistics. We present three models with an increasing number of explanatory variables. The first and second models utilise different aspects of past profitability information, while the third model includes additional predictors. Evidently, a large element of the next year's profitability is attributed to persistence, where the model that includes only past profitability explains 48% of next year's profitability. Nonetheless, adding predictor variables

Table 1. The table represents the descriptive statistics (in panel A) and the cross-sectional predictive regression of profitability (in panel B).

Var	Mean	p50	sd	p25	p75	Var	mean	p50	sd	p25	p75
IVOL	2.68	2.15	1.73	1.51	3.28	Amih	2.35	2.14	1.1	1.6	2.94
ROA_0	−0.01	0.05	0.25	−0.02	0.1	Zdays	0.16	0.1	0.14	0.03	0.28
EROA	−0.004	0.06	0.19	−0.03	0.09	Beta	1.21	1.06	1.31	0.44	1.81
ROA_{t+1}	−0.01	0.05	0.23	−0.02	0.1	Dbeta	1.33	1.11	1.99	0.27	2.18
PH52	0.76	0.83	0.22	0.64	0.94	BM	0.63	0.39	0.88	0.2	0.72
MAX	5.83	4.6	4.13	3.18	7.06	EP	−0.01	0.04	0.24	−0.01	0.07
MOM	1.94	5.16	39.4	−15	22.41	Delay	0.51	0.49	0.31	0.23	0.8
Last	−0.1	0.37	13.7	−6.5	6.88	I/K	1.22	0.27	3.85	0.15	0.62
MV	1614.4	262.8	4213.8	71.2	1033.8	CO12	11.46	9.22	31.78	−11.89	32.27
GA	0.28	0.08	0.87	−0.02	0.27	UCG	0.012	0.057	0.379	−0.14	0.228

	Profitability predictive regression										
Panel B:		ROA_0	Neg	Rev	PACC	TQ	D	D/B	DLife	Cons	R^2
Model1	Coeff	0.67[a]								0.0017*	0.48
	t-stat	70.44								1.63	
Model2	Coeff	0.67[a]	−0.05[a]	−0.28[a]						0.016[a]	0.52
	t-stat	51.44	−15.3	−30.89						12.62	
Model3	Coeff	0.56[a]	−0.02[a]	−0.19[a]	−0.0006[a]	−0.005[a]	0.13[a]	−0.018[a]	−0.06[a]	0.032[a]	0.55
	t-stat	49.1	−8.011	−24.29	−4.307	−6.923	22.75	−10.12	−35.95	20.6	

Ret is the monthly returns over the subsequent month, IVOL is the idiosyncratic volatility measured over the past 12 months, ROA0, EROA, and ROAt + 1 are the last year return on asset, the fitted value of return on asset, and the next year realised return on asset respectively, PH52 is the 52-week high ratio, Max is the average of 5 maximum daily returns over the three months, MOM is the return over the past 6 months, Last is the return over the last month, MV is the market value in millions of pound, GA is the growth in assets, Amih is logarithmic value of the Amihud price impact ratio, Zdays is the zero returns days, Beta is the market beta measured through the last 52 weeks, Dbeta is the down beta measured through the last 52 weeks, BM is the ratio of book equity to market value, EP id the earnings to price ratio, Delay is Hou and Moskowitz delay index, I/K is the ratio of capital expenditure plus research and development to capital, CO12 is the continuous overreaction measure of Byun, Lim, and Yun (2016), and UCG is unrealised capital gains. Also, in panel B, Neg is a dummy variable equal 1 if the firm has negative profitability and zero otherwise, Rev is the difference between the ROA in the last year and the average of ROA over the past 3 years, PACC is the percent accruals, T is Tobin's q, D is a dummy variable equal 1 if the firm does not pay a dividend in the last year and zero otherwise, D/B id the ratio of dividend to book equity, and DLife is a dummy variable equal 1 if the firm is in the introduction or decline or the growth stage (Dickinson 2011). a, b, and c indicate significance at 1%, 5%, and 10% respectively. The sample covers the period from January 1996 to December 2017.

does improve explanatory power, with Model 3 increasing the R-squared value to 55%. Thus, we employ future profitability predicted by Model 3 in the subsequent analysis.

The profitability estimates in Table 1 are similar to those reported for the US by Fama and French (2000, 2006), Hou and Robinson (2006) and Hou and van Dijk (2019). This similarity is both in the explanatory power and the estimated relations. Of note, profitability is persistent with an average lagged profitability coefficient of 0.56 (t-statistic = 49.1). Although persistent, profitability is mean reverting, with the reversion variable both negative (−0.19) and statistically significant (t-statistic = −24.3). Dividend policy significantly predicts future profitability, with the level of dividends positive and significant (coefficient = 0.133, t-statistic = 22.75). Thus, paying a higher dividend indicates higher future profitability. Equally, the dummy variable that takes a value of 1 for non-dividend payers and zero otherwise, is negatively related to future profitability. In contrast to theory, Tobin's Q is negatively related to future profitability with an average coefficient of −0.005 (t-statistic = −6.92). In seeking to explain this result, if investors are irrational, they may overreact to current investment levels such that stocks with a higher Tobin's Q (higher market value relative to book value) will generate lower profit in the future. Especially, given that we have controlled for other effects such as dividends, equity book value, and firm life cycle. Papanastasopoulos (2020) reports that percent accruals negatively predict future profitability of UK firms and our results confirm this. Accordingly, firms with higher accruals tend to be less profitable next year. This indicates that, on average, firms in initial and decline stages are significantly less profitable than ones in other development stages, a result supported by Dickinson (2011).

Table 2 presents the cross-section correlations coefficients between the variables. To briefly note some key correlations, expected profitability (EROA) is highly correlated with both IVOL and PH52. PH52 and EROA are positively correlated with a coefficient of 0.32, while IVOL is negatively correlated with PH52 (−0.58) and EROA (−0.51). Hence, stocks with high IVOL are more likely to receive negative market or fundamental-related news.

We also observe a negative correlation between IVOL and subsequent returns, which captures the IVOL puzzle. The relations between EROA, PH52, IVOL and the next year return is consistent with the idea of underreaction to fundamental news combined with limited attention, for which we observe an expected correlation.[7]

4.2. Portfolio analysis

Research reports a positive payoff for the zero-cost trading strategy that is long in high profitability and short in low profitability stocks (for example see, Novy-Marx 2013; Fama and French 2015; Ball et al. 2016). Nichol and Dowing (2014) confirm the existence of the profitably premium within the 350 biggest UK stocks. In these studies, profitability is measured using past observations. Kyosev et al. (2020) demonstrate that the premium associated with past accounting-based measures, such as profitability, is derived from their ability to project future growth. Therefore, we reconsider this premium using expected profitability (EROA) rather than past observations. We argue that the IVOL effect is a result of both fundamental (EROA) and market news. Thus, the performance of PH52 portfolios are also considered.

4.3. Sorting on EROA and PH52

We, separately, construct ten portfolios by sorting stocks, each month, into ten ascending deciles according to their EROA or PH52, such that, for example, Portfolio 10 contains stocks with the highest EROA while Portfolio 1 contains stocks with the lowest EROA. After forming these portfolios, their performance is measured by the average monthly returns over the next 3 and 12 months, skipping the first month after formation as well as the return difference and the risk-adjusted alpha from the Cahart 4-factor model. The portfolio returns are calculated using both equal and market value weighting and the results presented in Table 3.

Panel A presents the performance for the EROA based portfolios and the pattern of results shows that returns are increasing with EROA. Across time horizons and portfolio weighting, returns increase from the lowest to the highest EROA decile. For example, over the next 12 months, using market capitalisation weights, on average, stocks in the lowest decile of EROA will return −2.8%, while the stocks in the highest decile gain 0.69%. This 3.49% of differential returns is statistically significant at 1% level. This premium is also robust when adjusting for the Carhart (1997) risk factors. For example, for the same portfolio, the alpha equals 3.38% and is statistically significant at the 1% level. To ensure this pattern is not a result of the extreme deciles, a more conservative strategy that is long in the stocks with second-highest and short in the second-lowest EROA-based deciles is also tested. While this reduces the magnitude of the premium, it remains statistically significant with a Carhart alpha of 1.45%.

Of note, this expected profitability premium is largely attributed to the three smallest deciles. Moving from the 4th to the highest decile generates a noticeably smaller premium. Considering the equally-weighted returns over the next 3 months (EW_{2-4}), the returns difference between the lowest and 5th deciles is 2.9% whereas between the 5th to the highest decile, the difference is only 0.09%. This confirms a general conclusion in previous studies that the short-leg dominates many of the documented anomalies (Stambaugh, Yu, and Yuan 2012).[8]

The results in Panel B of Table 3 are similar to those in Panel A. Investing based on the 52-week high ratio (PH52) generates a premium similar to that for EROA. Notably, we observe an increasing pattern in returns associated with an increasing PH52 ratio. Considering value-weighted returns over the next 12 months and moving from the lowest to the highest PH52 decile, on average, the returns rise from −1.98% to 0.54%. Thus, a strategy that goes long in the stocks in the highest PH52 decile and short in stocks in the lowest PH52 decile, generates an economically and statistically positive premium of 2.55%. Adjusting this premium for the Carhart risk factors does not change the inference with an alpha of 1.76% and significant at the 1% level. Again, considering the more conservative strategy reduces, but does not eliminate, the magnitude and significance of the premium.[9] These results confirm prior findings in both the US and international markets (George and Hwang 2004; Liu, Liu, and Ma 2011). Moreover, as with EROA, the results show that the premium in the PH52 strategy is concentrated in the first (lowest) four deciles. The resemblance in the two strategies confirms the results in George, Hwang, and Li (2018), who suggest that the PH52 predictive power for the future returns is derived from the ability of PH52 ratio to project future profitability.

Table 2. The table represents the cross-sectional correlation between the variables.

Var	Ret_{t+1}	IVOL	$EROA_{t+1}$	ph52	ATT	ES5%	MAX	INF	Amih	ZDays	Mom12	CG	logV	PACC	TQ	D/B	LCycle
Ret_{t+1}	1																
IVOL	−0.19	1															
EROA	0.22	−0.51	1														
ph52	0.19	−0.58	0.32	1													
ATT	0.16	−0.42	0.32	0.55	1												
ES5%	−0.18	0.9	−0.45	−0.74	−0.42	1											
MAX	−0.18	0.96	−0.5	−0.47	−0.37	0.82	1										
INFUn	−0.17	0.65	−0.47	−0.42	−0.54	0.57	0.62	1									
Amih	−0.02	0.42	−0.22	−0.22	−0.21	0.4	0.42	0.39	1								
Zdays	−0.07	0.23	−0.23	−0.17	−0.35	0.18	0.26	0.61	0.23	1							
Mom12	0.08	−0.23	0.09	0.77	0.46	−0.47	−0.1	−0.15	−0.13	−0.06	1						
CG	0.11	−0.35	0.21	0.8	0.5	−0.52	−0.25	−0.25	−0.25	−0.11	0.82	1					
logV	0.15	−0.59	0.42	0.45	0.52	−0.55	−0.56	−0.86	−0.41	−0.63	0.22	0.32	1				
PACC	−0.05	0.06	0	−0.1	−0.05	0.09	0.04	0.04	−0.01	0.03	−0.08	−0.07	−0.03	1			
TQ	−0.17	0.13	−0.33	−0.13	−0.05	0.13	0.13	0.11	−0.05	0.01	0.02	0.02	−0.01	−0.02	1		
D/B	0.1	−0.28	0.35	0.17	0.19	−0.26	−0.27	−0.31	−0.13	−0.18	0.03	0.08	0.32	−0.08	0.01	1	
LCycle	−0.2	0.47	−0.73	−0.31	−0.31	0.42	0.47	0.47	0.21	0.24	−0.1	−0.2	−0.43	0.09	0.19	−0.28	1
INV	−0.07	0.19	−0.32	−0.12	−0.14	0.17	0.19	0.2	0.08	0.09	−0.03	−0.06	−0.18	0.04	0.15	−0.13	0.29

Ret12 is the average of monthly returns over the subsequent year, IVOL is the idiosyncratic volatility measured over the past 12 months, ROA_0, EROA, and ROA_{t+1} are the last year return on asset, the fitted value of return on asset, and the next year realised return on asset respectively, PH52 is the 52-week high ratio, Max is the average of 5 maximum daily returns over the three months, MOM is the return over the past 6 months, Last is the return over the last month, logv is the logarithm of market value in millions of pound, GA is the growth in assets, Amih is logarithmic value of the amihud price impact ratio, Zdays is the zero returns days, Beta is the market beta measured through the last 52 weeks, BM is the ratio of book equity to market value, EP id the earnings to price ratio, ATT id the indention index, INF is the information uncertainty index, I/K is the ratio of capital expenditure plus research and development to capital, CO12 is the continuous overreaction measure of Byun, Lim, and Yun (2016), and UCG is unrealised capital gains. The analysis cover the period from January 1996 to December 2017.

Table 3. The table represents the single sort analysis for the EROA and PH52.

	Sort on EROA												
Panel A:	Low	P2	3	4	5	6	7	8	P9	High	H-L	4Fα	P9-P2α
EW_{2-12}	−2.64	−1.91	−0.94	−0.3	0.11	0.23	0.29	0.3	0.39	0.08	2.73	2.37	1.92
t-stats											6.87	5.66	5.71
VW_{2-12}	−2.8	−1.38	−0.36	0.14	0.45	0.52	0.36	0.35	0.51	0.69	3.49	3.38	1.45
t-stats											6.2	6.27	4.24
EW_{2-4}	−2.65	−1.87	−1.02	−0.25	0.25	0.3	0.37	0.36	0.5	0.16	2.81	2.52	2.1
t-stats											6.07	6.72	5.86
VW_{2-4}	−2.54	−1.52	−0.29	0.18	0.43	0.41	0.57	0.3	0.48	0.78	3.32	3.37	1.89
t-stats											5.1	5.66	5.54
IVOL	4.63	4.02	3.12	2.53	2.21	2.03	1.95	1.92	1.99	2.1			
PH52	0.6	0.65	0.71	0.77	0.8	0.82	0.82	0.82	0.82	0.8			
INFUn	1.83	1.11	0.34	−0.13	−0.47	−0.63	−0.67	−0.72	−0.57	−0.30			
ATT	−0.78	−0.59	−0.27	0.02	0.20	0.29	0.30	0.34	0.36	0.33			
Mom	−7.57	−5.8	−1.85	4.76	8.57	8.41	8.16	8.72	9.59	8.97			
	sort on PH52												
Panel B:	Low	2	3	4	5	6	7	8	9	High	H-L	4Fα	P9-P2α
EW_{2-12}	−2.71	−1.94	−1.25	−0.73	−0.19	0.04	0.25	0.42	0.51	0.5	3.22	2.24	1.54
t-stats											7.03	5.43	4.41
VW_{2-12}	−1.98	−1.26	−0.42	−0.2	0.22	0.36	0.45	0.48	0.53	0.54	2.55	1.76	0.67
t-stats											3.96	3.57	1.8
EW_{2-4}	−3.13	−2.24	−1.32	−0.67	−0.18	0.14	0.45	0.66	0.76	0.79	3.92	2.96	2.19
t-stats											5.96	8.19	7.45
VW_{2-4}	−2.36	−1.47	−0.48	−0.12	0.22	0.43	0.55	0.58	0.53	0.62	2.99	1.81	0.87
t-stats											3.79	3.63	2.11
IVOL	4.97	3.74	3.11	2.67	2.39	2.22	2.08	1.99	1.92	2.06			
EROA	−0.13	−0.08	−0.04	0.00	0.02	0.03	0.04	0.05	0.05	0.05			
INFUn	1.61	0.76	0.33	−0.02	−0.24	−0.42	−0.54	−0.62	−0.65	−0.49			
ATT	−1.38	−0.83	−0.46	−0.15	0.06	0.29	0.46	0.59	0.75	0.89			
Mom	−89.55	−29.72	−8.75	3.25	11.89	19.48	25.44	30.14	35.50	43.87			

Each month, the stocks are sorted into 10 deciles according to the value of EROA or PH52. Then, the returns of these decile portfolios are measured as the value- or equal-weighted returns of the stocks included in the decile over the next 3 or 12 months skipping the first month after the portfolio formation. EW_{2-12} (EW_{2-4}) is the equally-weighted average monthly return over the next 12 (3) months, and VW_{2-12} (VW_{2-4}) is the value-weighted average monthly return over the next 12 (3) months, H-L is the deferential return between the highest decile and the lowest decile, 4Fα is the alpha with respect to the Carhart (1997) four-factor model, and P9-P2α is the Carhart-alpha of hedge strategy that goes long on the second-highest decile and short on the second-lowest decile. The t-stat is the Newey-West t-statistic the analysis cover the period from January 1996 to December 2017.

4.4. EROA and PH52 predictive power and the IVOL effect

The above shows that sorting stocks on EROA and PH52 generates a significant return premium, we now consider the impact of EROA and PH52 on the IVOL effect. Notably, we conjecture that the IVOL effect is a manifestation of the continued poor performance with low expected profitability and past returns. If investors anchor to past reference points on both fundamentals and market performance, they will miss information related to future performance. These cognitively erroneous expectations are stronger for the firms with prior bad news (Abarbanell and Bushee 1998; Riedl, Sun, and Wang 2021).

We condition the IVOL effect on EROA and PH52, separately and jointly. Each month, stocks are allocated equally into three portfolios according to the EROA or PH52, then, within each group, stocks are re-sorted into three further portfolios according to IVOL. Consequently, nine portfolios are created. Thus, we can test the magnitude of the IVOL effect across different levels of EROA or PH52. In addition, we test the joint EROA and PH52 effect on IVOL whereby, each month, stocks are allocated into two equal groups (Low & High) based on the EROA or PH52. Then, four intersection portfolios are created from these Low and High portfolios of EROA and PH52, e.g. stocks with Low EROA and Low PH52 will be in one portfolio and so forth. Next, within each one of these four portfolios, stocks will be allocated into three portfolios according to their IVOL value. Portfolio

Table 4. This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52.

	EROA then IVOL													
	EW							VW						
Panel A	IVOL Level							IVOL Level						
EROA	Low	M	High	H-L	t-stats	4Fα	t-stats	Low	M	High	H-L	t-stats	4Fα	t-stats
Low	−0.65	−1.81	−2.51	−1.86	−4.39	−1.86	−5.66	0.00	−1.76	−2.79	−2.79	−4.85	−2.88	−6.23
M	0.51	0.40	−0.46	−0.97	−3.65	−1.08	−5.27	0.56	0.46	−0.09	−0.65	−2.22	−0.71	−3.18
High	0.48	0.54	−0.27	−0.76	−3.14	−1.11	−5.16	0.50	0.52	−0.09	−0.59	−1.86	−1.16	−3.33
Diff				−1.10		−0.75					−2.20		−1.73	
t-stats				−4.06		−4.09					−5.24		−4.48	

	PH52 then IVOL													
Panel B	EW							VW						
PH52	Low	M	High	H-L	t-stats	4Fα	t-stats	Low	M	High	H-L	t-stats	4Fα	t-stats
Low	−0.88	−1.89	−2.83	−1.96	−5.70	−2.13	−6.88	−0.24	−1.28	−2.96	−2.72	−5.89	−2.88	−8.00
M	0.33	0.17	−0.90	−1.23	−3.69	−1.53	−5.84	0.44	0.31	−0.69	−1.14	−3.08	−1.72	−4.89
High	0.63	0.64	0.09	−0.53	−2.18	−1.22	−5.44	0.55	0.56	0.07	−0.48	−1.84	−1.41	−4.53
Diff				−1.42		−1.16					−2.24		−1.72	
t-stats				−5.89		−5.23					−5.58		−4.22	

		Joint effect of EROA and PH52 on the IVOL													
Panel	C	EW							VW						
PH52	EROA	L	M	H	H-L	t-stats	4Fα	t-stats	L	M	H	H-L	t-stats	4Fα	t-stats
Low	Low	−0.82	−1.92	−2.67	−1.85	−5.15	−1.99	−5.91	−0.17	−1.58	−2.87	−2.70	−5.56	−2.92	−7.28
	High	0.04	−0.09	−1.00	−1.04	−3.99	−1.25	−5.58	0.23	0.07	−0.81	−1.04	−2.76	−1.10	−5.12
High	Low	0.56	0.26	−0.60	−1.16	−3.70	−1.64	−5.64	0.49	0.31	−0.84	−1.33	−3.99	−2.05	−5.86
	High	0.60	0.69	0.56	−0.04	−0.24	−0.65	−3.29	0.56	0.67	0.49	−0.07	−0.29	−1.00	−3.40

Panels A & B show the double sort analysis of the IVOL effect within the different levels of the EROA or PH52. Firstly, each month, the stocks are sorted into tercile based on the EROA or PH52, then, within each tercile, the stocks are resorted into another three portfolios based on the IVOL. The performance of the IVOL effect is evaluated conditioning on the level of EROA or PH52. In Panel C, independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value- and equally-weighted differential returns between the highest and the lowest IVOL-based portfolio. The analysis spans the period from January 1996 to December 2017. t-stats is the Newey-West t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

performance is again measured by their average return over the next 12 months and for both raw returns and Carhart alpha.

The results are presented in Table 4, with the double sort analysis in Panels A and B, and triple sort in Panel C. The general pattern in Panels A and B reveals that the IVOL effect is diminishing in both EROA and PH52. Moving from the tercile of stocks with the lowest EROA (PH52) to the tercile of stocks with the highest EROA (PH52), the economic and statistical significance of the difference between the high and low IVOL group weakens. To illustrate, the value-weighted IVOL effect diminishes from −2.79% (t-statistic = −4.85) for the low EROA group to −0.59% (t-statistic = −1.86) for the high EROA group. The difference between the IVOL effect in low and the high EROA groups is −2.20% and statistically significant at 1% level. This finding is replicated with the Cahart risk-adjusted alpha, where again the IVOL effect is stronger in the low EROA and PH52 groups compared.

These results confirm the view that the IVOL effect is concentrated in stocks with poor expected profitability and market performance. Moreover, as observed in Table 3, these stocks exhibit a low attention index and poor performance in the past 12 months, while Table 4 suggests poor performance will persist over next 12 months. Collectively, these observations support underreaction behaviour as an explanation for the IVOL premium. Where investors are inattentive to news relating to future profitability, they underreact to positive news. Equally, results confirm the concentration of the IVOL effect within stocks with a low PH52 ratio, supporting prior studies linking PH52 predictability to investor anchoring bias (George and Hwang 2004; Li and Yu 2012).

This is consistent with prior evidence on investor mis-valuation of firms future profitability, undereaction to relevant news and anchoring to the past price (see, Setiono and Strong 1998; Jiang, Soares, and Stark 2016; Papanastasopoulos 2020).

Panel C of Table 4 reports the results of the triple sort on EROA, PH52 and IVOL.[10] This analysis examines the joint impact of EROA and PH52 on the IVOL effect. Of notable interest, the results reveal the absence of the IVOL effect in the raw return of stocks with both high EROA and PH52. Weighted either equally or by market value, the average monthly return over the next 12 months are near stable across the three IVOL-based portfolios generated within this group of stocks. To illustrate, the equally-weighted spread between the high IVOL portfolio and the low IVOL portfolio is indistinguishable from zero with a value of −0.04% (t-statistic = −0.24). However, this absence of the IVOL effect in the raw returns does not hold for the Cahart risk adjusted results. Here, for the high EROA and PH52 group of stocks, the risk-adjusted alpha of the IVOL long-short strategy is −0.65 (t-statistic = −3.29) for the equally-weighted portfolios and −1.00% (t-statistic = −3.4) for the value-weighted.

These findings show that market-based information, proxied by PH52, and fundamental-based information, proxied by EROA, jointly, determine a large part of the IVOL effect. For raw returns, the IVOL anomaly disappears for high EROA and PH52 stocks. This supports our view that both market- and fundamental-based information are required to explain the IVOL effect, while individually they are unable to. Regarding the significant Cahart alpha, this suggest the potential need for additional factors, which we return to later.

4.5. Fama and MacBeth cross-section regression

In the above portfolio sorting technique it quickly becomes difficult to control for a large number of variables; even sorting on two variables can leave the constructed portfolios with a low number of stocks. To address this issue, we utilise the approach of Fama and MacBeth (1973). In this two-stage method, the association between future returns and IVOL, EROA, and PH52 are analysed while controlling for a large set of other predictors. In the first stage, the following regression is fitted on monthly basis:

$$R_{it+k} = \alpha_t + B_{1t}\mathrm{IVOL}_{it} + B_{2t}\mathrm{PH52}_{it} + B_{3t}\mathrm{EROA}_{it} + \sum_{j=1}^{J} \gamma_j Z_{jit} + \varepsilon_{it+k} \tag{4}$$

where $R_{\mathrm{it+k}}$ denotes the average monthly return over the next $k = 3$ or 12 months for stock i, with t the current month. $\mathrm{IVOL}_{\mathrm{it}}$ is the idiosyncratic volatility, $\mathrm{PH52}_{it}$ is the 52-week high, $\mathrm{EROA}_{\mathrm{it}}$ is the expected profitability, Z_{jit} is a vector of control variables (listed in the Appendix) and ε_{it+k} is an error term. For comparison and robustness, Equation (4) is estimated across different sets of variables. In the second stage, a monthly time-series of the estimated coefficients is generated and these time-series are tested for statistical significance (using Newey-West t-statistics), with results presented in Table 5.

The analysis is performed using the average monthly returns over the next 3 and 12 months, skipping the first month after the variable measurement date. The results for the control variables are suppressed to save space. The results reconfirm the idiosyncratic volatility puzzle, with a negative and significant relation between IVOL and future realised returns. Columns 1 and 2 (C1 & C2) of Table 5 show that the average slope coefficients for subsequent stock returns over 3 and 12 months on the current IVOL are −0.72 and −0.66 respectively.

The results under columns C3 and C4 and then C5 and C6 confirm those in Table 3 regarding the IVOL effect together with EROA and PH52 individually. C3 and C4 confirm the positive EROA-return predictive relation, while C5 and C6 confirm the positive PH52-return relation. In each case, while the magnitude and degree of statistical significance of the IVOL coefficient is reduced, it remains both negative and significant. However, when we include both EROA and PH52, columns C7 and C8, the IVOL coeffient, while still negative, becomes statistically insignificant (at the 5% level) and much reduced in magnitude. This, again, supports our view that both the fundamental-based expected profitability and market-based price signal are important in explaining the IVOL effect.

The same inference is maintained across the remaining columns (C9 to C14) when allowing for additional control variables, including the interaction between EROA and PH52. Both EROA and PH52 maintain a positive

Table 5. This table represents the Fama-MacBeth cross-sectional regression.

	C1	C2	C3	C4	C5	C6	C7	C8
VARIABLES	R3M	R12M	R3M	R12M	R3M	R12M	R3M	R12M
IVOL	−0.72***	−0.66***	−0.53***	−0.47***	−0.28**	−0.32***	−0.12	−0.15*
t-stats	(−4.95)	(−5.49)	(−4.32)	(−4.53)	(−2.59)	(−3.33)	(−1.34)	(−1.84)
EROA			3.13***	3.46***			2.760***	3.22***
t-stats			(5.11)	(6.10)			(4.96)	(5.99)
PH52					4.98***	3.71***	4.84***	3.57***
t-stats					(7.90)	(7.17)	(7.92)	(7.02)
Constant	1.47***	1.29***	0.99***	0.78***	−3.56***	−2.48***	−3.85***	−2.82***
t-stats	(4.71)	(4.63)	(3.24)	(2.74)	(−5.09)	(−4.07)	(−5.43)	(−4.55)
Control	no	no	no	no	no	no	no	no
Observations	133779	133779	133779	133779	133779	133779	133779	133779
R-squared	0.055	0.083	0.066	0.101	0.083	0.115	0.093	0.131

	C9	C10	C11	C12	C13	C14
VARIABLES	R3M	R12M	R3M	R12M	R3M	R12M
IVOL	−0.07	−0.11	−0.18	−0.12	0.05	0.0858
t-stats	(−0.75)	(−1.39)	(−0.919)	(−0.78)	(0.31)	(0.62)
PH52	3.09***	2.59***	5.2***	4.85***	3.76***	3.76***
t-stats	(4.94)	(4.29)	(4.08)	(4.76)	(3.80)	(5.096)
EROA	1.84***	2.4***	4.12***	4.13***	3.69***	3.77***
t-stats	(2.89)	(4.15)	(3.17)	(4.23)	(3.24)	(4.73)
PH52∗EROA			−5.72***	−5.47***	−4.78***	−4.58***
t-stats			(−3.65)	(−4.45)	(−3.7)	(−4.72)
EROA∗IVOL			−0.52	−0.513*	−0.61**	−0.63***
t-stats			(−1.6)	(−1.953)	(−2.12)	(−2.6)
PH52∗IVOL			−0.32	−0.47**	−0.56***	−0.68***
t-stats			(−1.1)	(−1.98)	(−2.63)	(−4.12)
EROA∗PH52∗IVOL			1.41***	1.34***	1.37***	1.32***
t-stats			(3.10)	(3.50)	(3.63)	(3.84)
Constant	−2.49***	−2.38***	−3.06***	−2.92***	−2.61**	−2.9***
	(−2.78)	(−3.03)	(−2.68)	(−3.30)	(−2.49)	(−4.08)
Control	yes	yes	no	no	yes	yes
Observations	130869	130869	133779	133779	130869	130869
R-squared	0.16	0.20	0.10	0.14	0.17	0.212

The table reports the average slope coefficients and the corresponding newey-west t-statistic. Each month, the stocks are regressed on the IVOL, EROA, PH52, and a list of control variables. the list of control variable includes Maximum returns(MAX), the return over the past 6 months (MOM), the return over the last month (Last), the logarithm of market value in millions of pound (Logv), the growth in assets (GA), the logarithmic value of the amihud price impact ratio (Amih), the zero-returns days (Zdays), the market beta (Beta), the down beta (Dbeta), the ratio of book equity to market value (BM), the earnings to price ratio (EP), the information uncertainty index (INF), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017.

*, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

and significant effect on subsequent returns, while IVOL is insignificant. Of interest, the interaction term of EROA∗PH52∗IVOL is positive and significant across four different specifications and suggests for a given level of EROA and PH52, the return predictability of EROA and PH52 is amplified by higher IVOL. This is consistent with the reported arbitrage-friction role of the high idiosyncratic volatility (Pontiff 2006; Au et al. 2009). Further, the negative coefficients on EROA∗IVOL and PH52∗IVOL interactions indicate reversion within stocks.

The above discussion suggests that the IVOL effect is largely a manifestation of inattentive investor response to news revealed by price-based and fundamentals signals regarding a stock's prospects. As an example, Table 4, Panel C shows that for stocks with inconsistent profitability signals (e.g. Low EROA and High PH52 or the reverse) and a high IVOL generate, on average, negative returns over the next 12 months. This suggests that investors focus their limited cognitive ability on only one of these information signals (i.e. fundamental or market) and neglect the information content of the other (see, Peng and Xiong 2006). Consequently, investors overestimate the prices of these informationally uncertain stocks. Further, the results may be explained by anchoring bias, where investors form expectations about future cash flow depending on a past reference point. For instance, George and Hwang (2004) argue that investors believe there is no further room for movement in the direction of the past price-trend when the current stock price is near or far from its past 52-week high. Consequently, investors erroneously underestimate the likelihood of the price moving further up (down) when close to (far from) the past 52-week high and underreact to the continuing trend and price-momentum emerges (also see, Hao et al. 2018).

5. Further issues and robustness tests

We now consider further analysis of our key results, together with a battery of robustness tests including (i) time series analysis and alternative risk models, (ii) alternative proxy for expected profitability, (iii) subsamples analysis, (iv) alternative explanation.

5.1. Time series analysis: EROA and PH52 as factors

We consider a model with pricing factors that mimic the cross-section premium for the EROA and PH52 strategies. This checks whether the explanatory power of EROA and PH52 holds in a time-series setting. We examine whether monthly excess returns generated by EROA and PH52 mimicking portfolios better explain the IVOL effect compared to alternative risk factors.

We follow the traditional factor-construction method of Fama and French (1993) and use the widely known models of Carhart (1997) and Hou, Xue, and Zhang (2015) to provide a comparison. To these, we add two factors constructed to mimic the EROA and the PH52 return predictive power. Thus, on a monthly basis, stocks are sorted into three groups according to the EROA and PH52 with sample breakpoints for the bottom 30%, middle 40%, and upper 30%. The EROA and the PH52 factors are rebalanced monthly.

Table 6 presents the IVOL effect after controlling for different pricing characteristics. Panel A, for one-month ahead returns, shows that adding EROA and PH52 to the Cahart 4-factor model, reduces the alpha of an IVOL based strategy from -2.71 (t-statistic $= -3.6$) to -1.39 (t-statistic $= -1.9$). This reduction in the IVOL effect is an indication of the significant impact of the EROA and PH52 factors on IVOL. Adding the investment factor does not noticeably impact the IVOL effect. The results of the Q5F model only reduce alpha slightly to -1.34 (t-statistic $= -1.92$). The comparison with Hou, Xue, and Zhang (2015)'s 4-factor model (Q5F vs Q4F) produce similar explanatory power for the IVOL effect. The results in Panel B, for 12-month ahead returns, show that the IVOL effect, in terms of both raw returns and Carhart alpha, disappears once EROA and PH52 factors are included. This is consistent with both the above portfolio sorting and Fama-MacBeth approaches and reveals that both EROA and PH52 explain a large part of the short-term IVOL effect and subsume it over the longer period.

Table 7 represents the Gibbons, Ross & Shanken (GRS; 1989) joint test of asset pricing performance. The testing assets are the ten IVOL portfolios. Under this test, the joint explanatory power of a specific pricing model is examined against the null hypothesis that all alphas of the priced trading strategies are zero. The results indicate that, at the 5% significance level, the GRS test is not significant (with a value of 1.83) for the $4F_{Eroe\&PH}$ model. In comparison with the widely used Carhart 4-factor model, the models that add EROA and PH52 produce a substantially lower absolute alpha and higher explanatory power.[11]

5.2. Alternative measures of profitability

The above analysis is conducted using our obtained measure of EROA. Here, we consider the robustness of the results using alternative measures of accounting profitability. Following Hou, Xue, and Zhang (2015), we first consider returns on equity (ROE). Second, following Fama and French (2015), we employ operating profitability (OP), which is measured as operating earnings scaled by lagged book equity. Third, we use cash operating profitability (COP), measured as operating earnings minus working accruals divided by book assets. Ball et al. (2016) demonstrate that COP is a more powerful returns predictor than the other accounting profitability measures.

Obtaining the expected profit measure in the same way as for EROA, Table 8 presents the adjusted-alpha of IVOL long/short strategy conditional on the level of the PH52 and one of the alternative expected profitability measures. The results confirm those found for EROA. Namely, the IVOL effect is concentrated in stocks with

Table 6. The table represents the single sort analysis for the IVOL.

Panel A	IVOL effect Next 1-month										
Variable	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	H-L
RP	0.22	0.29	0.3	0.46	−0.07	−0.13	−0.42	−0.97	−2.07	−3.82	−4.04
Car4F	−0.22	−0.03	−0.1	0.2	−0.28	−0.25	−0.39	−0.6	−1.43	−2.68	−2.71
t-stats	−1.56	−0.23	−0.64	0.94	0.27	−0.94	−1.05	−1.57	−2.92	−3.76	−3.6
$4F_{Eroe\&PH}$	−0.34	−0.22	−0.23	0.23	−0.25	−0.01	0.13	0.28	−0.49	−1.48	−1.39
t-stats	−2.28	−1.48	−1.26	1.02	−0.88	−0.01	0.42	0.76	−1.03	−2.31	−1.9
Q5F	−0.34	−0.26	−0.24	0.23	−0.24	0.04	0.2	0.2	−0.4	−1.42	−1.34
t-stats	−2.31	−1.73	−1.32	1.03	−0.84	0.14	0.65	0.65	−0.89	−2.17	−1.92
Q4F	−0.31	−0.13	−0.1	0.31	−0.21	−0.03	−0.12	0.05	−0.44	−1.37	−1.32
t-stats	−1.93	−0.87	−0.53	2.66	1.43	0.94	0	0.15	−1.02	−2.07	−1.89
Panel B	Next 12-month										
Variable	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	H-L
RP	0.24	0.24	0.24	0.23	0.06	−0.08	−0.53	−1.1	−2.35	−2.89	−3.13
Car4F	−0.02	−0.09	−0.2	−0.14	−0.2	−0.48	−1.08	−1.33	−2.37	−1.81	−1.97
t-stats	−0.1	−0.64	−1.68	−1.02	−1.26	−3.09	−3.28	−3.9	−5.01	−2.89	−2.81
$4F_{Eroe\&PH}$	−0.44	−0.52	−0.56	−0.34	−0.42	−0.15	−0.31	0	−0.56	0.08	0.27
t-stats	−2.26	−2.52	−2.38	−1.99	−1.76	−0.78	−1.06	0.01	−0.97	0.18	0.55
Q5F	−0.38	−0.52	−0.53	−0.49	−0.47	−0.17	−0.17	0.1	−0.55	−0.11	0.02
t-stats	−2.25	−2.5	−2.28	−2.47	−1.76	−0.86	−0.57	0.25	−0.85	−0.21	0.04
Q4F	−0.43	−0.4	−0.49	−0.34	−0.38	−0.19	−0.64	−0.46	−1.33	−0.15	−0.02
t-stats	−1.82	−1.71	−2.15	−1.72	−1.45	−0.78	−1.75	−1.01	−2.37	−0.33	−0.04

Each month, the stocks are sorted into 10 deciles according to the value of IVOL. Then, the returns of these decile portfolios are measured as the value-weighted returns of the stocks included in the decile over the next 1 or 12 months skipping the first month after the portfolio formation. H-L is the differential return between the highest decile and the lowest decile, Car4F is the alpha with respect to the Carhart (1997) four-factor model, $4F_{Eroe\&PH}$ is the alpha of model that includes the market, the size, the ph52, and the EROA factors, Q5F is the alpha of model that includes the market, the size, the ph52, the EROA factors, and the investment factors, and Q4F is the alpha with of the Hou, Xue, and Zhang (2015) Q-factor model. The t-stat is the Newey-West t-statistic the analysis cover the period from January 1996 to December 2017.

Table 7. This table represents the overall pricing performance of the proposed 4FEroe&PH and Q5F models and the Carhart (1997) 4-factor model and the Hou, Xue, and Zhang (2015) Q-factor model.

Model	Av(α)	GRS	p(GRS)	Av(Rsq)	SE(α)	IαI	SR(α)
Car4F	−0.578	3.079	0.001	0.629	0.281	0.617	0.374
$4F_{Eroe\&PH}$	−0.238	1.832	0.056	0.650	0.280	0.366	0.301
Q5F	−0.207	1.798	0.061	0.650	0.282	0.371	0.300
Q4F	−0.222	1.490	0.143	0.640	0.283	0.293	0.270

The test assets are the excess return of the 10 IVOL-based decile portfolios. The table reports the average alpha (Av), the Gibbons, Ross, and Shanken (1989) joint test (GRS), the probability value of the GRS test (p (GRS)), and the average of determination coefficients (Av (Rsq)), the standard error of alpha, the average of absolute alpha (IαI), and the Sharpe ratio of the corresponding alpha (SR (α)). the analysis covers the period from January 1996–2017.

low expected profitability and a price far from the 52-week high. Moreover, the IVOL effect is strongest with both low expected profitability (EROE, ECOP or EOP) and low PH52.

Table 9 presents the Fama-MacBeth cross-section regression of stock returns for each of the alternative profitability measures. The general observation is that, like EROA, the different measures of profitability positively predict returns over the next 3 and 12 months. The average slope coefficient for the expected profitability measures range from 0.764–3.465 and are statistically significant. However, it is noticeable that the effect of these profitability measures on IVOL appear to be weaker than for EROA (in Table 5), especially for the 12 months horizon. For example, Column M10 shows that when controlling for EOP and PH52, the average slope coefficient for IVOL is −0.216 and statistically significant. However, after including the control returns predictors, the IVOL predictive power becomes insignificant.

Table 8. This table represents the analysis of the IVOL effect conditional on the levels of one of the three profitability alternative measures and PH52.

			EROE			ECop			EOP		
PH52	Ex		RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$
L	L	H-L	−2.82	−2.05	−0.17	−2.97	−2.03	−0.08	−2.76	−1.75	0.17
		t-stats	−5.28	−3.13	−0.42	−5.51	−3.38	−0.19	−5.03	−2.59	0.41
	H	H-L	−1.32	−1.26	−0.34	−1.55	−1.20	−0.28	−1.34	−1.23	−0.38
		t-stats	−4.08	−2.98	−0.49	−4.96	−3.64	−0.43	−4.05	−2.96	−0.51
H	L	H-L	−1.64	−1.32	−0.43	−1.44	−1.69	−0.73	−1.45	−1.35	−0.47
		t-stats	−3.83	−3.10	−1.03	−3.37	−3.86	−2.12	−3.29	−3.14	−1.17
	H	H-L	−0.29	−0.45	−0.04	−0.34	−0.57	−0.03	−0.29	−0.51	−0.12
		t-stats	−1.28	−1.65	−0.14	−1.43	−1.98	−0.10	−1.24	−1.70	−0.40

We use the return on book equity (EROE), the cash-based profit on the book asset (ECop), and the operating profit on book equity (EOp) as alternatives to ROA. Independently, each month, the stocks are sorted into two groups based on the expected profitability (EROE, ECop, and EOp) and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value- and equally-weighted differential returns (over the next 12 months) between the highest and the lowest IVOL-based portfolio. The table reports the value-weighted performance measures of the IVOL hedge strategy (H-L). The RP is the excess returns, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of the model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats are the Newey-West t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

5.3. Subsample analysis

In this subsection, we consider our main analysis under different sampling conditions, (i) microcap stocks are removed from the sample, (ii) the effect across different sentiment states, (iii) the full sample will be divided between two sub-periods.

5.4. Do micro-cap stocks matter?

It is argued that many documented asset pricing anomalies are concentrated in stocks with an extremely small market capitalisation (microcaps stocks) (see, Fama and French 2008). Therefore, we consider the robustness of our results to the exclusion of such microcaps. Table 10 repeats part of the analysis from Table 4 while excluding stocks with a market capitalisation less than £25 million. These excluded stocks constitute approximately 10% of the sample. While this criterion is arbitrary, it is selected in order to balance the desire to control for microcaps and maintaining an acceptable sample size and broadly follows previous work. For example, Fama and French (2008) and Papanastasopoulos (2020) suggest that small and micro stocks compromise the lowest 10% of market capitalisation. While Bali and Cakici (2008) sort the stocks into quantiles according to the market value and allocate the stocks in the lowest quantile into the small group. As noted, our threshold of £25 million is close to the bottom 10% of the total market capitalisation.

In comparison to Table 4, the results in Table 10 indicate that microcaps have little influence on the magnitude or significance of the IVOL effect. The table reveals that the long/short IVOL strategy is strongest when both the EROA and PH52 are at their lowest levels, and weakest (and insignificant) when they are both at their highest levels. As an example, using value-weighted portfolis and for stocks with both low EROA and PH52, the IVOL effect over the next 12 months is −3.17% and significant, while this drops to an insignificant −0.4% for stocks with high EROA and PH52. Table 11 presents the cross-section regression of future stock returns against IVOL, PH52 and EROA, again excluding microcap stocks. The results are highly similar to those in Table 5 for the full sample. The IVOL effect significantly depends on the levels of EROA and the PH52.

5.5. Sentiment

Prior studies suggest that investor mispricing depends on investor sentiment. Baker and Wurgler (2007) and Stambaugh, Yu, and Yuan (2015) demonstrate that investors are more likely to overprice stocks when optimistic.

Table 9. This table represents the Fama-MacBeth cross-sectional regression.

	EROE				ECOP				EOP			
Model	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
VARIABLES	R3M	R12M	R12M	R12M	R3M	R12M	R12M	R12M	R3M	R12M	R12M	R12M
IVOL	−0.167*	−0.193**	−0.101	0.0921	−0.141	−0.173*	−0.098	0.0468	−0.193*	−0.216**	−0.107	0.14
t-stats	(−1.726)	(−2.134)	(−1.268)	0.723	(−1.420)	(−1.896)	(−1.266)	0.348	(−1.930)	(−2.38)	(−1.340)	1.051
PH52	4.873***	3.590***	2.623***	3.688***	4.896***	3.620***	2.697***	3.340***	4.928***	3.636***	2.659***	3.505***
t-stats	−7.82	−7.02	−4.421	4.372	−7.817	−7.086	−4.565	3.953	−7.866	−7.091	−4.501	4.221
ExProfit	1.130***	1.409***	1.423***	3.195***	2.376***	2.708***	2.389***	3.465***	0.764***	1.014***	1.0***	3.951***
t-stats	4.367	6.076	5.553	4.553	4.283	5.593	4.285	4.209	4.216	6.042	5.527	4.598
PH∗IVOL				−0.541***				−0.503**				−0.636***
t-stats				(−3.189)				(−2.317)				(−3.341)
ExProfit∗IVOL				−0.829***				−0.574**				−0.815***
t-stats				(−3.667)				(−2.393)				(−3.276)
ExP.∗PH52∗IVOL				1.134***				1.003**				1.434***
t-stats				3.934				2.562				3.868
ExProfit∗PH52				−3.229***				−3.821***				−4.443***
t-stats				(−3.898)				(−3.415)				(−3.723)
Constant	−3.833***	−2.806***	−2.419***	−3.038***	−4.080***	−3.053***	−2.632***	−2.705***	−3.888***	−2.884***	−2.504***	−2.900***
t-stats	(−5.259)	(−4.380)	(−3.067)	(−4.024)	(−5.557)	(−4.820)	(−3.231)	(−3.587)	(−5.309)	(−4.489)	(−3.189)	(−4.269)
Control	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes
Observations	133762	133762	130865	130865	132690	132690	129891	129891	133687	133687	130804	130804
R-squared	0.09	0.13	0.20	0.21	0.09	0.13	0.20	0.21	0.09	0.12	0.19	0.21

The table reports the average slope coefficients and the corresponding newey-west t-statistic. Each month, the stocks are regressed on the IVOL, one of the alternative measures of the expected profitability (EROE, ECop, and EOp), PH52, and a list of control variables. the list of control variable includes Maximum returns(MAX), the return over the past 6 months (MOM), the return over the last month (Last), the logarithm of market value in millions of pound (Logv), the growth in assets (GA), logarithmic value of the amihud price impact ratio (Amih), the zero-returns days (Zdays), the market beta (Beta), the down beta (Dbeta), the ratio of book equity to market value (BM), the earnings to price ratio (EP), the information uncertainty index (INF), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017.

*, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table 10. This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52 excluding the stocks with a market value of less than 25 million pounds, independently, each month, the stocks are sorted into two groups based on the EROA and the PH52.

			IVOL with PH and EROA					
Panel A			Next 3 months VW returns					
PH	EROA		L	M	H	RP	Car4F	$F4_{Roa\&PH}$
L	L	ret	−0.14	−1.46	−2.97	−3.07	−2.41	−0.89
		t-stats	−0.39	−2.00	−3.65	−5.53	−4.19	−1.73
	H	ret	0.24	0.08	−0.81	−1.3	−0.45	−0.03
		t-stats	0.75	0.17	−1.42	−3.05	−1.1	−0.04
H	L	ret	0.49	0.31	−0.87	−1.61	−1.72	−0.73
		t-stats	2.31	1.13	−1.9	−4.69	−4.01	−2.31
	H	ret	0.56	0.67	0.48	−0.32	−0.61	−0.3
		t-stats	3.1	2.51	1.37	−1.28	−4.19	−0.99
Panel B			Next 12 months VW returns					
PH	EROA		L	M	H	RP	Car4F	$F4_{Roa\&PH}$
L	L	ret	−0.16	−1.53	−3.08	−3.17	−1.97	−1.14
		t-stats	−0.37	−1.83	−3.21	−4.31	−2.93	−2.04
	H	ret	0.22	0.25	−0.79	−1.27	−0.55	−0.146
		t-stats	0.57	0.48	−1.27	−2.97	−1.38	−0.38
H	L	ret	0.59	0.37	−0.48	−1.28	−1.05	−0.7
		t-stats	2.37	1.21	−0.85	−3.49	−2.77	−1.91
	H	ret	0.58	0.75	0.43	−0.4	−0.16	−0.08
		t-stats	2.93	2.39	0.98	−1.19	−0.62	−0.26

Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value- and equally-weighted differential returns between the highest and the lowest IVOL-based portfolio. The RP is the excess returns, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of the model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats is the Newey-West t-statistic and $4F\alpha$ is the alpha with respect to the Carhart (1997) four-factor model.

To consider this, investor sentiment data is represented by the Economic Sentiment Indicator published by the European Commission for the UK market. To subtract the rational component, this index is orthogonalised to the monthly change in industrial production, the change in the consumer price index, the unemployment rate and the term premium between the 10-year Treasury bonds and 3-month Treasury bills.[12]

Table 12 presents the relation between the IVOL effect and the joint levels of EROA and PH52 across different sentiment states. The full period is classified into three sub-periods depending on a 3-month rolling average of the sentiment series, pessimistic (bottom 30%), mild (middle 40%), and optimistic (upper 30%). The figures represent the IVOL long/short strategy. Consistent with overpricing behaviour, the IVOL effect is significantly stronger in the optimistic state, especially for stocks with low PH52. For stocks with prices far from their 52-week high, following a period of high sentiment, the excess return on the IVOL strategy is −3.58% (t-statistic = −9.09) and −1.81% (t-statistic = −9.46) for the low and high EROA groups respectively. The corresponding figures for the pessimistic period are −1.15% (t-statistic = −3.94) and 0.03% (t-statistic = 0.1).

This result is consistent with the cognitive dissonance phenomenon documented by Antoniou, Doukas, and Subrahmanyam (2013), which states that news that is inconsistent with current market sentimental diffuses slowly. Thus, the continuation in loser performance is stronger during high sentiment periods due to the overpricing of these stocks. This is also consistent with Riedl, Sun, and Wang (2021) who note investor tendency to understate the persistence of firm losses during high sentiment periods. Comparing stocks with low EROA and PH52 to stocks with high EROA and PH52, the difference in excess returns of the long/short IVOL strategy is more than doubled from −1.36% to −2.97% in an optimistic period, with a significant difference of −1.61%.

Table 11. This table represents the Fama-MacBeth cross-sectional regression.

Model	M1	M2	M3	M4	M5	M6
VARIABLES	R3M	R3M	R12M	R12M	R3M	R12M
IVOL	−0.134	−0.0849	−0.17*	−0.1	−0.022	−0.004
	(−1.34)	(−0.78)	(−1.93)	(−1.19)	(−0.117)	(−0.03)
PH52	4.83***	2.96***	3.58***	2.62***	3.87***	3.44***
	7.60	4.77	6.38	4.37	3.31	5.11
EROA	2.95***	2.025***	3.46***	2.59***	3.19***	2.92***
	5.46	3.29	6.52	4.6	2.72	4.39
EROA∗IVOL					−0.32	−0.31
					(−1.09)	(−1.41)
PH52∗IVOL					−0.58**	−0.61***
					(−2.133)	(−3.810)
PH52∗EROA∗IVOL					1.074**	1.03***
					2.45	3.08
PH52∗EROA					−4.26***	−3.72***
					(−2.94)	(−4.43)
Constant	−3.82***	−2.23**	−2.79***	−2.20**	−2.33**	−2.35***
	(−5.47)	(−2.35)	(−4.32)	(−2.54)	(−2.03)	(−3.12)
control	no	yes	no	yes	yes	yes
Observations	119,705	117,347	119,705	117,347	117,347	117,347
R-squared	0.091	0.167	0.124	0.203	0.178	0.212

The table reports the average slope coefficients and the corresponding newey-west t-statistic. Firms with a value less than 25 million pounds are excluded. Each month, the stocks are regressed on the IVOL, one of the alternative measures of the expected profitability (EROA), PH52, and a list of control variables. the list of control variable includes Maximum returns(MAX), the return over the past 6 months (MOM), the return over the last month (Last), the logarithm of market value in millions of pound (Logv), the growth in assets (GA), the logarithmic value of the amihud price impact ratio (Amih), the zero-returns days (Zdays), the market beta (Beta), the down beta (Dbeta), the ratio of book equity to market value (BM), the earnings to price ratio (EP), the information uncertainty index (INF), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017.

*, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

5.6. Pre- vs post-crisis

Table 13 presents the IVOL effect over two sub-periods, 1996–2008 and 2009–2017. The results here remain broadly consistent both across the two sub-periods and with those reported above. Specifically, we continue to observe the IVOL effect in both raw returns and the alpha obtained from the Cahart 4-factor model, while the effect disappears when adding the EROA and PH52 factors into the explanatory model. Perhaps as expected, there is some greater evidence of poor performance associated with the IVOL long/short strategy in the period spanning from 1996 to 2008. During this period, the UK market (and globally) experienced two significant financial crises, the dotcom crash (2000–2002) and the global financial crisis (2007–2008). However, this is typically manifest in terms of larger coefficient values rather than statistical significance. An interesting observation that requires further confirmation is the apparent reversal of the IVOL effect for the high EROA and PH52 portfolio in this latter period.

5.7. Alternative explanations

Prior studies suggest different explanations for the inverse return effect associated with high idiosyncratic volatility. Investor overreaction is considered as one plausible explanation where, for example, investors overreact to stocks with lottery-like features. Bali, Cakici, and Whitelaw (2011) suggest the maximum daily returns over the past months (MAX) acts as a proxy for the lottery feature. They find that the IVOL effect is fully absorbed by this measure. Byun, Lim, and Yun (2016) point out that continuous overreaction led by investor overconfidence could be the reason behind price momentum. Polk and Sapienza (2009) provide evidence on the catering hypothesis of investment decisions. They find that higher capital expenditure signals an overpricing in the market. Accordingly, capital expenditure predicts reversal in subsequent stock returns.

Therefore, we consider whether our results can be attributed to overreaction behaviour. In Table 14, overreaction proxies are added to the cross-section regression of stock returns over the next 12 months against the

Table 12. This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52, while conditioning on sentiment states.

			IVOL Effect within PH52 & EROA								
			Pessimistic			Optimistic			Optim-Pessim		
PH	EROA		RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$
L	L	Ret	−1.15	−1.58	−0.19	−3.58	−2.56	−1.05	−2.43	−0.98	−0.86
		t-stat	−3.94	−3.31	−0.45	−9.09	−2.46	−1.47	−2.8	−1.01	−1.18
	H	Ret	0.03	−0.23	0.29	−1.81	−0.7	−0.23	−1.85	−0.47	−0.52
		t-stat	0.1	−0.4	0.35	−9.46	−1.79	−0.47	−2.95	−0.63	−0.64
H	L	Ret	−0.95	−1.79	−0.93	−1.81	−1.32	−0.37	−0.86	0.47	0.56
		t-stat	−3.91	−3.41	−2.91	−7.18	−8.28	−0.82	−1.47	0.8	1.21
	H	Ret	0.22	−0.56	−0.33	−0.6	−0.52	−0.3	−0.82	0.04	0.03
		t-stat	1.41	−2.06	−1.15	−3.29	−1.2	−0.65	−2.27	0.1	0.13
		Diff	−1.36	−1.02	0.14	−2.97	−2.04	−0.75	−1.61	−1.03	−0.89
		t-stat	−2.95	−2.42	0.31	−4.79	−2.23	−0.94	−2.04	−1.14	−1.23

Using a ranking of an investor sentiment index, the Pessimistic state is the months in the bottom 30% while the Optimistic state is months in the upper 30%. Independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value-weighted differential returns between the highest and the lowest IVOL-based portfolio. The RP is the excess returns, Diff is the difference between the IVOL hedge portfolio performance within the low EROA and low PH52 group and the high PH52 and high EROA group, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats is the Newey-West t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

Table 13. This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52 during two different sub-periods of 1996–20008 and 2009-2107.

IVOL effect with PH and EROA								
			1996–2008			2009–2017		
PH52	EROA		RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$
L	L	Ret	−3.1	−1.5	−0.65	−2.73	−1.68	−1.08
		t-stat	−4.53	−3.53	−1.64	−4.13	−2.18	−0.54
	H	Ret	−1.85	−0.53	−0.04	−0.48	−0.51	−0.65
		t-stat	−3.21	−1.07	−0.06	−1.69	−1.14	−0.74
H	L	Ret	−1.82	−1.34	−0.99	−1.23	−0.46	0.42
		t-stat	−3.84	−3.23	−3.21	−2.82	−0.85	0.6
	H	Ret	−0.59	−0.56	−0.72	0.08	0.81	1.3
		t-stat	−1.55	−2.36	−2.63	0.33	2.19	2.16
		Diff	−2.5	−1.5	0.06	−2.8	−3.4	−2.38
		t-stat	−7.91	−4.56	0.12	−7.38	−4.71	−1.83

Independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value-weighted differential returns between the highest and the lowest IVOL-based portfolio. The RP is the excess returns, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of the model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats is the newey-west t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

IVOL, EROA, PH52 and interaction terms between them. Confirming our findings, Table 14 supports the ability of EROA and PH52 to predict returns over the next 12 months and to affect the inverse IVOL-return relation. The average slope coefficients are positive and highly significant for the EROA, PH52 and PH52∗EROA∗IVOL. Except for the continuous overreaction (CO12) variable, results suggest that the overreaction proxies also significantly predict returns. Controlling for the effect of EROA and PH52, the average slope coefficients on MAX and the investment to capital ratio (I/K) is −0.49 (t-statistic = −1.98) and −0.48 (t-statistic = −2.09) respectively. Of interest, the (I/K) variable affects the interaction terms with IVOL (EROA∗IVOL and PH52∗IVOL), both becoming insignificant at the 5% level. This supports the interpretation that the significance of interaction terms (PH52∗IVOL and PH52∗EROA) is derived by the reverse side of the IVOL effect. Specifically, these results

Table 14. This table represents the Fama-MacBeth cross-sectional regression with overreaction proxies.

	M1	M2	M3	M4	M5	M6	M7	M8
IVOL	−0.123	−0.01	−0.141	−0.15	−0.119	−0.131	−0.175	−0.156
	(−0.78)	(−0.6)	(−0.86)	(−1.0)	(−0.71)	(−0.86)	(−1.11)	(−0.98)
EROA	4.13***	3.860***	4.171***	3.802***	3.876***	3.590***	3.835***	3.593***
	4.23	4.06	4.34	4.07	4.13	3.91	4.143	3.942
PH52	4.85***	4.73***	4.677***	4.44***	4.48***	4.37***	4.26***	4.12***
	4.76	4.88	4.67	4.73	4.71	4.84	4.59	4.62
EROA∗IVOL	−0.513*	−0.468*	−0.541**	−0.453*	−0.49*	−0.418	−0.476*	−0.435*
	(−1.953)	(−1.80)	(−2.12)	(−1.72)	(−1.95)	(−1.62)	(−1.86)	(−1.73)
PH52∗IVOL	−0.47**	−0.455**	−0.482**	−0.39	−0.50**	−0.38	−0.407*	−0.393*
	(−1.99)	(−1.98)	(−2.05)	(−1.69)	(−2.01)	(−1.68)	(−1.76)	(−1.74)
PH52∗EROA∗IVOL	1.34***	1.40***	1.39***	1.22***	1.45***	1.28***	1.28***	1.34***
	3.50	3.611	3.73	3.16	3.85	3.27	3.43	3.53
PH52∗EROA	−5.47***	−5.44***	−5.51***	−4.93***	−5.47***	−4.94***	−4.99***	−4.98***
	(−4.45)	(−4.5)	(−4.61)	(−4.22)	(−4.64)	(−4.26)	(−4.34)	(−4.38)
MAX		−0.490**			−0.536**	−0.402*		−0.454*
		(−1.982)			(−2.197)	(−1.745)		(−1.959)
CO12			0.205		0.269*		0.228	0.282*
			1.305		1.721		1.54	1.884
I/K				−0.481**		−0.443**	−0.452*	−0.413*
				(−2.09)		(−1.990)	(−1.934)	(−1.815)
Constant	−2.922***	−2.639***	−2.913***	−2.438***	−2.601***	−2.234***	−2.441***	−2.203***
	(−3.302)	(−3.071)	(−3.272)	(−2.945)	(−3.006)	(−2.739)	(−2.900)	(−2.662)
Observations	133,779	133,779	131,633	133,779	131,633	133,779	131,633	131,633
R-squared	0.14	0.142	0.144	0.145	0.149	0.149	0.152	0.156

The table reports the average slope coefficients and the corresponding newey-west t-statistic. Each month, the stock returns over the next 12 months are regressed on the IVOL, the expected profitability (EROA), the PH52, the interaction terms between the IVOL, the EROA, and the PH52, and overreaction proxies (MAX, CO12, and I/K). MAX is the average of 5 maximum daily returns over the past 3 months, I/K is the ratio of capital expenditure plus research and development to capital, and CO12 is the continuing overreaction measure of Byun, Lim, and Yun (2016). The analysis covers the period from January 1996 to December 2017.

*, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

indicate that investor speculation on stocks with lottery features and/or high investment rates generate part of the documented IVOL effect. Stocks with high volatility are found to be attractive for individual investors with lottery features preference (Boyer, Mitton, and Vorkink 2010). Also, Malagon, Moreno, and Rodríguez (2015) link the idiosyncratic volatility anomaly to firm investment and investor preference for skewness.

Polk and Sapienza (2000) argue that firm managers cater to investor overvaluation of the firm price by pumping an abnormal amount of money into firm capital which leads to inefficient capital allocation and poor subsequent performance. In light of the above findings, investor overreaction to attention-grabbing events, such as extreme returns and a firm's excessive investment contributes to the magnitude of the IVOL effect. Therefore, it seems that the inverse relation between IVOL and the future realised returns is more complex than only being represented by underreaction without considering overreaction-related mispricing. As such, we conclude that the IVOL puzzle involves complex behaviour that represents mispricing behaviour across both underreaction and overreaction.

6. Summary and conclusion

This paper investigates the joint ability of fundamental- and market-based news to explain the underperformance of stocks with high idiosyncratic volatility (IVOL effect). Specifically, we test whether the underperformance of stocks with high IVOL is due to investor response to bad news related to expected accounting profitability (measured as the out-of-sample prediction of future profitability) and the nearness of a stock's current price to its past 52-week high price. A sample of stocks from the UK market over the period from January 1996 to 2017 is analysed. The IVOL has emerged as one of the more concerning anomalies for our existing asset pricing models as the negative returns for high IVOL stocks contradicts such theories. As such, understanding the nature of the IVOL puzzle is crucial for our understanding of asset pricing and building efficient portfolios.

The empirical results based on sorting stocks show that the IVOL effect is strongest when investors receive bad market news (i.e. low PH52) and low projected future profitability (i.e. low EROA). In contrast, the IVOL effect is subsumed, both economically and statistically, by both good market news and profitability expectations but not when considering just one effect. Moreover, this pattern is stronger following periods of high investor sentiment. Results from Fama-MacBeth cross-section regressions further support the view that the information content from both expected profitability and 52-week high ratio subsumes the IVOL effect. The same inference is reached by a time-series analysis.

These findings suggest that the negative IVOL-return relation is triggered by investors slow response to news related to firm prospects. This arises as investors pay less attention to news regarding persistently underperformed stocks and anchor to previous beliefs. Combining underreaction with high information uncertainty (high IVOL) deters arbitraging activities and leads to slow correction and a persistent downward trend in the prices of these stocks. Consequently, the IVOL-returns inverse relation emerges in the market.

The empirical results presented here have important implications for both practitioners and academics. The evidence indicates the opportunity to build a profitable strategy based on revealed information. Going long in stocks with low IVOL and good signals (high 52-week high ratio and high expected profitability) and short in stocks with high IVOL and weak signals (low 52-week high ratio and low expected profitability) creates a profitable strategy to investors in the UK market. Screening out stocks with high IVOL from general winners could generate a more stable momentum strategy. Moreover, results from the time-series analysis show that considering additional factors (i.e. profitability and the 52-week high) to the pricing model (e.g. Carhart 4-factor model) add explanatory power. For the academic community, the results suggest some important directions for future research. The relations highlighted may explain some of the anomalous pricing behaviour documented in the UK market. For example, Lu and Hwang (2007) and Foran, Hutchinson, and O'Sullivan (2015) document a counter-intuitive underperformance of illiquid stocks in the UK market. Stocks with bad performance signals and high IVOL are expected to be illiquid.

The empirical findings presented here also encourages future work to extend the pricing modelling by testing the ability of factors based on expected profitability and the 52-week high ratio to explain other reported pricing anomalies. This could also be extended to additional pricing models and stock markets. As a further avenue for future research, our results demonstrate that expected profitability and the 52-week high ratio are both separatedly priced and their joint inclusion explains the IVOL effect. While the former variable is clearly linked to fundamentals, the latter is more indicative of a behavioural pricing factor and this is supported by its statistical signficance. However, some work (e.g. George, Hwang, and Li 2018) argues that the 52-week high ratio may also be predictor for profitability. Therefore, alternative variables to capture the behavioual effect may be identifiable.

Notes

1. IVOL-related anomalies are pricing behaviours that are shown to exhibit a close link to IVOL in the existing literature, notably, the lottery-like effect (see, Bali, Cakici, and Whitelaw 2011).
2. While not directly addressing the same question as here, related work includes Clubb and Naffi (2007) and Lin and Lin (2019).
3. This includes, Fama and French (2015, 2016), Hou, Xue, and Zhang (2015) and Novy-Marx (2013).
4. Previous work (e.g., George and Hwang 2004; Marshall and Cahan 2005; Liu, Liu, and Ma 2011; Hao et al. 2018) supports the 52-week high ratio as a predictor for stock returns and argues it results from anchoring behaviour by investors (e.g., Li and Yu 2012; Huang, Lin, and Xiang 2020).
5. See http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/.
6. Furthermore, by analyising the 52-week high ratio while controlling for expected profitability, this supports our argument that the former reporesents the irrational component and is not subsumed by the latter.
7. This attention index is built by extracting the first principal component of the three attention proxies, namely, the change in trading volume, the Hou and Moskowitz (2005) delay measure, and the information discreteness index in the notion of Da et al. (2022). Thus, this index does not include the information in PH52 ratio.
8. Related studies show that the past profitability premium is a manifestation of erroneous investor expectations regarding the future cash flows (for example, see, Wang and Yu 2013; Min et al. 2018). This view can be supported by observing a similar pattern in both idiosyncratic volatility (IVOL) and information uncertainty (INFUn) through the EROA deciles. Both IVOL and INFUn barely change over the highest 6 deciles (5th decile to highest) then they start to increase continuously from the 5th decile to lowest.

9. Of note, a large part of this reduction in the magnitude of the premium will be due to the inclusion of momentum in the Carhart model.
10. A key concern when building portfolios of this type, with numerous sorting, is the number of stocks in each portfolio. A table in Appendix 2 notes the average number of stocks in each of the twelve portfolios and ranges from approx. 32 to 52. These are the smallest (most sorts) portfolios used in our analysis.
11. As an aside, it is important to note that the intention of this analysis is not to claim that EROA and the PH52 are pricing factors (a goal that is beyond the scope of this study). Rather, it is to support that previous cross-section analysis with a time series evidence on the significant association between the IVOL effect and both EROA and PH52.
12. The data source is DataStream.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix 1 – Firm control variables

Control variables

To ensure robust results and to isolate the potential effect of other return predictors, we include a a set of control return predictors that are widely documented in the literature.

1- Unrealised capital gains: following Grinblatt and Han (2005), the unrealised capital gains are measured as follow,

$$\text{UCGt} = \frac{P_{-1} - R_{-1}}{P_{-2}}, \tag{6}$$

where P_{-1} is the stock price at the end of the last month, and

$$\text{R} - 1 = \frac{1}{k}\sum_{n=1}^{750}\left(V_{-1-n}\prod_{k=1}^{n-1}[1 - V_{-1-n-k}]\right)P_{-1-n} \tag{7}$$

where k is constant that makes the weights on past prices sum to one, V_{-j} is the daily turnover at the previous j days from the end of month t. in this work, the UCG is measured using the past three years data.
2- Book-to-market ratio BM: is the ratio of the book equity to the market value of equity.
3- Earnings-to-price ratio (EP): is the ratio of earnings per share to the price per share.
4- Market value (MV): is the market capitalisation of the firm.
5- Growth in assets: following and Cooper, Gulen, and Schill (2008) and Hou, Xue, and Zhang (2015), the growth in assets is measured using the year-on-year percentage change in total assets.
6- Market Beta: traditionally measured by regressing the stock's risk premium (R_i-r_f) on the market risk premium (R_m). To mitigate the impact of nonsynchronous trading, we follow Lewellen and Nagel (2006) and Cederburg and O'Doherty (2016) by adding four lags of the market premium to the regression, as a following,

$$Rp_{i,t} = \alpha\text{i} + \beta_{i,t} * Rp_{m,t} + \sum_{n=1}^{4}\beta_{i,t-n} * Rp_{m,t-n} + \varepsilon_{i,t},$$

$$\beta_i = \beta_{i,t} + \sum_{n=1}^{4}\beta_{i,t-n} \tag{8}$$

where Rp_i and Rp_m is the weekly risk premium for the stocks i and the market portfolio, respectively, and β_i is the estimated beta. The beta will be re-estimated monthly using the weekly returns over the past 12 months.
7- Downside Beta (Dbeta): is a systematic let-tail risk proxy, measured in a similar way to the market beta, however, the stock returns are regressed on the negative market returns rather than the whole market returns series.
8- Med-term Momentum (Mom): following, Jegadeesh and Titman (1993), med-term momentum is defined as the cumulative return over the past 6 months after skipping a month between the portfolio formation period and the holding period.
9- Short-term reversal (Rev): following Jegadeesh (1990), this variable is measured using the stock return at the end of the past month.
10- Maximum return: following Bali, Cakici, and Whitelaw (2011) the maximum returns are employed as a proxy for the lottery characteristic and defined as the average of 5 maxim daily returns over the past 3 months.
11- Continuous overreaction index (CO): this variable is developed by Byun, Lim, and Yun (2016) to capture the trend in the investors' overconfidence. They define this measure as following,

$$\text{CO}_{i,t} = \frac{\text{sum}(w_j \times \text{SV}_{i,t-j}, \ldots\ldots\ldots\ldots\ldots.., w_1 \times \text{SV}_{i,t-1})}{\text{mean}(\text{VOL}_{i,t-j}, \ldots\ldots\ldots\ldots\ldots.., \text{VOL}_{i,t-1})} \tag{9}$$

where $\text{SV}_{i,t}$is the signed volume for stock i in month t,

$$\text{SV}_t = \begin{cases} \text{VOL}_t & \text{if } r_t > 0, \\ 0 & \text{if } r_t = 0, \\ -\text{VOL}_t & \text{if } r_t < 0, \end{cases} \tag{10}$$

where VOL_t is the dollar volume in month t and r_t is the stock return in month t, J is the length of formation period, and w_j is a weight that takes a value of $J\text{-}j+1$ in month $t\text{-}j$ (i.e. $w_j = 1$ and $w_1 = J$). In this work, the continuous overreaction (CO) is measured using a 12-month formation period.

12- Investment-capital ratio (I/K): is a proxy of firm investment and defined as follow,

$$I/K = \frac{I_{t-1}}{K_{t-2}} \tag{11}$$

where I is the sum of capital expenditure and research and development expense, and K is net property, plant, and equipment.

13- Price impact ratio: following Amihud (2002) and Florackis, Gregoriou, and Kostakis (2011), this liquidity measure is defined as,

$$RtoTR_{i,t} = \Sigma\ \{|R_{i,\,d}|/TR_{i,d}\}, \tag{12}$$

where $R_{i,t}$ is the return of stock i in day d, and $TR_{i,d}$ is the daily trading turnover for the stock I in day d.

14- Zero-return days: this liquidity proxy is measured over the past 12 months as the number of days with zero returns to the total number of trading days.

15- Delay response measure: is Hou and Moskowitz (2005) delay measure., which defined as,

$$\text{Delayi} = 1 - \frac{R^2_{\text{unrestriscted}}}{R^2_{\text{restricted}}}, \tag{13}$$

where $R^2_{\text{unrestriscted}}$ is the fraction of stock return explained by the market model with 4 lag terms, and $R^2_{\text{restricted}}$ is the fraction of returns explained by the traditional market model (i.e. CAPM). The higher value of Delay indicates a higher predictive ability for the past information, therefore a more delayed response to that information available in the market.

16- Shock to the volume: Low abnormal trading volume signals low visibility of stocks (Gervais, Kaniel, and Mingelgrin 2001). Specifically, the abnormal volume of stock i in month t is

$$\text{ABnVi} = \left(\text{Volume}_{it} - \sum_{n=1}^{12} \text{Volume}_{it-n}\right) / \text{ Std (Volumei)} \tag{14}$$

Where Volume is the pound trading volume in month t, Std is the standard devotion of the volume over the past 12 months. Equation (6) allows us to define the degree of drop and rise in the trading activity of a particular stock. According to this equation, if they pay little attention to stocks i, they should trade this stock less frequently.

17- Information risk Index: It is more likely for individual investors to pay less attention to complex and difficult-to-process information (Hirshleifer, Hsu, and Li 2017). Zhu et al. (2019) found that both limited attention and information asymmetry are important in explaining the documented fundamental-based anomaly. We employ 5 different proxies of information uncertainty. These proxies are firm size, firm age, and turnover volatility, return synchronicity, and the bid-ask spread. To summarise the common component of these uncertainty proxies we employ the PCA to extract the first common component of these proxies which will be used as the index of information uncertainty.

(i) Firm size: the frim size is represented by the market value of the firm which is the number of shares outstanding multiplied by the closing price.
(ii) Age: In this study, the Firm's age is the number of months since the firm initial appearance in the DataStream database.
(iii) Turnover volatility: George and Hwang (2010) demonstrate that stocks with high turnover volatility are more likely to be overvalued stocks due to the high information uncertainty these stocks show. To evaluate the turnover uncertainty we measure the standard deviation of the daily turnover over the past 12 months.
(iv) Bid-Ask spread: The daily bid-ask spread is the difference between the closing bid and ask prices divided by their average. We take the average of daily bid-ask spread over the past year.
(v) Return Synchronicity: In their categorical learning model, Peng and Xiong (2006) link the return co-movement to the limited attention capacity by the investors. Following Chue et al (2019), return synchronicity Defined as,

$$\text{Synch } = \text{Log}\left(\frac{R^2}{1-R^2}\right), \tag{15}$$

where R^2 is the coefficient of determination of the standard Market model (CAPM).

Appendix 2 – Average number of stock in each key portfolio

The following table documents the average number of stocks in each portfolio.

	Low PH52			High PH52		
	Low IVOL	Mid IVOL	High IVOL	Low IVOL	Mid IVOL	High IVOL
Low EROA	51.94	51.60	51.25	33.27	32.93	32.59
High EROA	32.48	32.22	31.86	52.56	52.20	51.84