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Revisiting the Idiosyncratic Volatility Puzzle and MAX Effect in European Equity Markets

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Abstract

In light of traditional financial theory's argument that firm-specific risk should not impact future returns, the findings of the Idiosyncratic Volatility (IVOL) puzzle, as well as the Maximum Daily Returns (MAX) effect, have sparked a vibrant academic debate. Using data from January, 1993, to December, 2022, this paper presents European aggregate and country-level evidence at the intersection between the two asset pricing anomalies. For IVOL, we show a persistent significant anomaly across most European countries, which proves robust for different portfolio formation strategies and sorting controls, as well as the exclusion of microcaps. In line with existing literature, we confirm the mechanical relationship between the two anomalies for European data, however, we find evidence for bivariate MAX/IVOL sorts contradictory to Bali et al. (2011).

Keywords: Idiosyncratic volatility, Fama-French three-factor model, MAX effect, European equity markets, Asset pricing anomalies

JEL Codes: G11, G12, G15

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1 Introduction

The Capital Asset Pricing Model (CAPM)[1] states that investors should not be rewarded for risk that could be diversified away, i.e. risk specific to a firm. Only systematic risk should be compensated with higher returns. While this implies that there is no meaningful relationship between idiosyncratic risk and returns, recent research has shown a remarkable negative correlation between the two, which has been labelled as the Idiosyncratic Volatility puzzle (henceforth IVOL puzzle) (Ang et al., 2006, 2009). Subsequent conflicting findings around the existence and direction of relation between the two have resulted in a vibrant academic debate, suggesting the need for further empirical research.

After Ang et al.'s initial study in 2006 focused only on U.S. data, strong international evidence has been published in an extension paper shortly after. Performing a quintile portfolio sort, the authors identify that the difference in returns between the highest and lowest quintile portfolio sorted on IVOL is -1.31%[2] per month globally (Ang et al., 2009). That said, the extension paper only presents results on European, Asian, and on a global level. The only exception are country-level results for the G7 countries. The first main purpose of this paper is therefore to focus on the findings on the idiosyncratic volatility puzzle with regards to European developed markets, and more specifically present country-level characteristics.

As a second contribution to the academic literature, this study tries to bridge the results from Ang et al. (2006, 2009) with the striking findings of the Maximum Daily Return (MAX) effect (Bali et al., 2011). The MAX effect states that the maximum daily return of a stock correlates negatively with future returns, inferring that investors show a preference for lottery-like pay-outs with the chance of exceptionally high returns. This in turn drives up prices and lowers future returns. Employing bivariate sorts on extreme returns and idiosyncratic volatility, and firm-level cross-sectional regressions, Bali et al.

[1] The CAPM was first introduced by William Sharpe, John Lintner, and Jan Mossin in consecutive articles from 1964 to 1966.

[2] This value represents global results including the U.S., which drives the results. Excluding the U.S., the global difference in returns between extreme portfolios is reduced to -0.67%, while Europe shows a slightly higher value of -0.72%. The sample period for international data ranges from $1980-2003$, with some exceptions starting in the mid-1980s, while U.S. data covers the years $1963-2003$.

(2011) reverse the findings of Ang et al. (2006, 2009). Equally-weighted portfolios display a statistically significant *positive* relationship between idiosyncratic volatility and returns, when first sorted on maximum returns.

Ang et al.'s methodology will be closely followed, and further complemented with more recent data and findings from related studies. Using portfolio sorts on European country-level data, $L/M/N$ trading strategies are used to draw conclusions. We sort portfolios on three methodologies, namely Total Volatility (TVOL), IVOL, and MAX. Further, we perform a variety of robustness tests for firm-specific characteristics, asset pricing factors, subsamples, and different trading strategies over an array of time periods.

The results suggest that the IVOL puzzle persists across most European countries, with an average difference in returns between the extreme quintile portfolios of -0.74% (-0.55%) for value-weighted (equally-weighted) portfolios. Moreover, we find similar results for the MAX effect, albeit at slightly lower statistical significance levels. The results are accompanied by highly significant differences in CAPM and FF3 alphas across all three sorting methodologies for both equally- and value-weighted portfolios.

In the following, the most important research literature related to Ang et al. (2006, 2009) as well as the findings of Bali et al. (2011) will be summarised, before the methodology and the European data used to replicate the study are laid out in the third section. Section four will present and discuss the empirical findings of this paper, before a conclusion is reached.

2 Literature review

The following section gives a brief overview of the main paper that this study is based on. Subsequently, a more holistic literature review on the topic of the idiosyncratic volatility puzzle is presented. Finally, the literature review delves into a summary and related articles of the MAX effect paper by Bali et al. (2011). The latter sections focus on more recent literature presented in reaction to the reference papers.

2.1 Ang, Hodrick, Xing, & Zhang's findings from 2006 & 2009

The first papers attesting importance to the relationship between idiosyncratic volatility and expected returns date back to 1978. Levy (1978) finds that in an imperfect market where investors cannot hold all available securities, idiosyncratic risk is positively correlated with returns. Similarly, Merton (1987) suggests that market frictions lead to an investor's inability to fully diversify away idiosyncratic risk, therefore resulting in higher expected returns for high idiosyncratic volatility stocks[3].

In their paper from 2006, Ang et al. study how volatility affects cross-sectional returns. In a first section, systematic volatility is examined. It is, however, the second section that presents puzzling findings about the relationship of idiosyncratic risk in relation to expected returns. While previous papers have either found no relationship or a positive relationship, Ang et al. (2006) present a *negative* relationship. That said, the authors' biggest criticism about the previous literature's findings on a positive relationship is the lack of individual stock-level analyses and that none of the studies sort the portfolios used for return calculations directly on idiosyncratic volatility.

Defining idiosyncratic risk as the standard deviation of the residual after regressing daily return data on the Fama-French three-factor model (FF3), the authors sort the stocks into quintile portfolios. The authors use daily U.S. stock data ranging from 1963 to 2000, which is also subsetted in a second step to examine shorter time frames according to economic cylces. Comparing the highest idiosyncratic volatility quintile portfolio with

[3]Both Levy (1978) and Merton (1973, 1987) start their approach by relaxing the assumptions of the CAPM, which originally does not ascribe any relationship between idiosyncratic volatility and returns.

the lowest for the 1/0/1 strategy[4] yields a monthly average difference in raw return of −1.06%, with a difference in FF3 alphas of −1.31%.

Testing for robustness, the authors also perform double-sorting to control for Size, Book-to-Market, Leverage, Liquidity, Volume, Turnover, Bid-Ask Spreads, Coskewness, Dispersion in Analysts' Forecasts, and Momentum. Before sorting on IVOL relative to FF3, the authors form quintiles based on the firm-specific characteristic and then average the IVOL quintiles across the quintiles resulting from the initial sort. Next to controlling for firm-specific characteristics, trading strategies with estimation and holding periods longer than one month are tested to counteract the potential short-term effects specific events such as results announcements or changes in management may have on the stock's volatility and return. While the magnitude of correlation changes between trading strategies, the direction and significance is consistent among all[5]. Lastly, different subsamples of the data set have been analysed to see if the IVOL puzzle persists over and during different times. Different decades, times of economic expansion, stability, and recession[6] all show a highly significant negative correlation, thus further supporting the authors' findings.

In an extension paper from 2009, the authors gather supporting evidence of the idiosyncratic volatility puzzle outside the U.S. in 23 developed markets. Country-level results are only reported for the G7 countries, while the remaining results are on European, Asian, and global level. Given the dominance of the U.S. equity market over the rest of the world, global and G7 results are presented including and excluding the U.S. findings. The main difference to the 2006 paper is the use of Fama-MacBeth regressions, as well as the presentation of value- and equally-weighted portfolios. The extension paper also goes further in trying to lay out potential explanations of the negative relationship between idiosyncratic volatility and future returns, but concludes that no specific economic phenomenon can sufficiently explain the puzzle[7]. Finally, the authors note that the strong co-movement

[4]Ang et al. (2006) employ a set of $L/M/N$ strategies, with an estimation period of L months, a waiting period of M months, and a holding period of N months. The portfolio formation strategy is described in more detail in Section 3.1.3.

[5]Ang et al. (2009) show results for 1/1/1, 1/1/12, 12/1/1, 12/1/12.

[6]Expansions and recessions are defined as per the National Bureau of Economic Research (NBER).

[7]Here, Ang et al. look at the U.S. data in more detail and examine whether private information (Easley and O'hara, 2004), transaction costs (Lesmond et al., 1999), analyst coverage (Hou and Moskowitz, 2005),

between U.S.'s and the global results suggest an underlying global economic factor capable of explaining the idiosyncratic volatility puzzle (Ang et al., 2009).

2.2 Further research on idiosyncratic volatility

2.2.1 Findings on a negative relationship

Upon Ang et al.'s publications, several other authors sought to confirm the puzzling findings on idiosyncratic volatility. Guo and Savickas (2006) perform decile portfolio sorts on quarterly CRSP data after running FF3 regressions. Citing Ghysels et al. (2005), they see quarterly data as a better basis for the estimation of idiosyncratic volatility as it mitigates distorting effects of too-short-term data. The authors find a jointly significant negative relationship of idiosyncratic volatility and stock market volatility on future returns, but fail to prove individual statistical significance. In a subsequent iteration of their paper from 2006, Guo and Savickas (2008) stress the strong co-movement of idiosyncratic volatility between the U.S. and other countries. As stocks which are new and/or have a smaller market capitalisation tend to have higher idiosyncratic volatility due to lower liquidity, Guo and Savickas (2010) shift their focus from equally-weighted to value-weighted portfolios and follow Ang et al. (2006, 2009) in constructing quintile portfolios based on one-month lagged idiosyncratic volatility estimations. The authors obtain very similar results to Ang et al. (2009), albeit imposing slightly altered data filters and examining different time periods. Finally, Guo and Savickas (2010) show that the idiosyncratic volatility puzzle holds for U.S. data prior to 1962 as well as more recent data for G7 countries.

Han and Lesmond (2011) argue that the relationship of idiosyncratic volatility and expected returns rests on estimation errors in connection to liquidity costs. In their view, the bid-ask bounce[8] leads to inflated IVOL estimates. Furthermore, the authors quote zero return observations as a second reason for why the loadings on systematic risk factors might be biased, which in turn leads to a biased estimate of IVOL. Regressing stock

institutional ownership (Kumar, 2009), delay (Hou and Moskowitz, 2005), and skewness (Barberis and Huang, 2008), have explanatory power on the puzzle. While some of the aforementioned factors change the regression results, the Fama-MacBeth coefficient on idiosyncratic volatility stays negative and significant.

[8] See for example Blume and Stambaugh (1983).

returns on the Carhart (1997) four-factor model yields a significant negative relationship only before controlling for the bias induced by the bid-ask bounce. That said, the authors obtain results in line with Ang et al. (2006) that are robust to the controls when forming value-weighted portfolios with Fama and MacBeth (1973) regressions.

Chen and Petkova (2012) argue that the underlying explanation for the idiosyncratic volatility puzzle is the factor of innovations in average stock variance. The price of this risk factor is negative, and the loading on high (low) idiosyncratic volatility stocks is positive (negative), confirming the negative relationship found by Ang et al. (2006). The authors find that when including innovations in average stock variance as a factor to the FF3 model, idiosyncratic volatility becomes insignificant. From an economic point of view, the authors interpret the average stock variance as a measure for economic uncertainty.

Stambaugh et al. (2015) replicate Ang et al. (2006) findings and see a potential explanation in the relative pricing of stocks. In combination of the two concepts of arbitrage risk and arbitrage asymmetry, the authors argue that the idiosyncratic volatility puzzle persists more strongly in stocks that are overpriced and exists with reversed signs in most underpriced stocks, albeit at lower significance levels. Further, the returns of penny stocks and of stocks with low institutional ownership − both are proxies for stocks that are less easily shorted − show an even stronger negative correlation to idiosyncratic volatility[9]. On aggregate level, the authors argue that the idiosyncratic volatility effect is even more pronounced for overpriced stocks in times of a market-wide tendency for overpricing, and vice versa for underpriced stocks. The results hold when controlling for smaller firms and employing an equally-weighted portfolio formation strategy.

Hou and Loh (2016) use Fama and MacBeth (1973) regressions by regressing different "candidate explanatory variables" on the IVOL-measure on a single-stock level and try to quantify the explanatory power of each of the potential explanations on the IVOL puzzle. Their regression results are in line with Ang et al. (2006), as they find a highly significant negative relationship. Further, they find that 11 out of 12 potential explanatory variables

[9] See also Brandt et al. (2010) on the evolution of idiosyncratic volatility and its concentration among retail investor-held stocks; and Boehme et al. (2009) who use similar controls.

cannot individually explain the idiosyncratic volatility puzzle[10]. In a second step, the authors combine several potential explanatory variables in a multivariate analysis, yet they show that a sizeable portion of the puzzle remains unexplained.

Chen et al. (2020) present recent support of Ang et al. (2006). The authors focus on the potential effect of microstructure noise within stock sample selection. Since many opposing studies argue that the IVOL anomaly is driven by noise, proxied by microcaps or penny stocks, the authors separate those stocks and find weak evidence for the IVOL anomaly. For stocks with less microstructure noise, the findings are significant across different portfolio formation approaches (value-weighted and equally-weighted).

In relation to the research in support of the findings of Ang et al. (2006), an interesting contribution is made by Bali et al. (2018) and Fenner et al. (2020). In contrast to the more broadly adopted cross-sectional ranking, the authors apply an intertemporal ranking of stocks with unusually high (low) IVOL (IVOL shocks). A stock with higher (lower) IVOL than usual is ascribed a positive (negative) IVOL shock. This ranking methodology leads to more heterogeneous portfolios and sheds light on investors' behaviour considering news or quiet periods. The authors find that selling stocks with positive IVOL shocks and buying stocks with negative IVOL shocks yields a statistically significant risk-adjusted return for both equally-weighted and value-weighted portfolios, albeit at smaller magnitude in the latter case.

Finally, a number of country-specific papers have been published on the topic. Elvelin and Hage (2015) examine country-level data from Sweden to confirm the findings of Ang et al. (2006). The authors closely follow the same methodology and perform a battery of robustness tests. Further, Aboulamer and Kryzanowski (2016) find a positive relationship for both IVOL as well as the MAX effect in Canada. Even after controlling IVOL for the MAX effect (i.e., performing double-sorts), the positive relationship persists. The authors indicate that the Canadian stock market is home to considerably less anomalies, pointing at local, country-specific drivers behind the IVOL puzzle. Another study by Nartea et al. (2010) publishes only weakly significant findings for the ASEAN countries, further sug-

[10] The 12^{th} explanatory variable is the maximum daily return following Bali et al. (2011), which still yields highly significant results for IVOL but reverses the sign.

gesting that stock market anomalies tend to show different behaviour between developed and emerging markets. Drew et al. (2006) examine the relationship by constructing a multifactor model akin to Fama and French (1993). They limit their research to the German and UK equity markets and find a positive relationship between IVOL and returns.

2.2.2 Findings on a positive relationship

Spiegel and Wang (2005) show that IVOL and liquidity have opposing signs in relation to expected returns. The authors use monthly data from the U.S. and find that while expected returns decrease with rising liquidity, the effect is offset by a stronger positive relationship between IVOL and expected returns.

Fu (2009) argues that the lagged idiosyncratic volatility used by Ang et al. (2006) is not a good estimate of expected idiosyncratic volatility. The author states that the low autocorrelation of IVOL, as well as the absence of random walks for individual stocks' IVOL, calls for the prediction of future IVOL rather than the estimation based on lagged values. Employing exponential generalised autoregressive conditional heteroskedasticity (EGARCH) models, the author finds a significantly positive relation between *expected* IVOL and expected returns. As an economic reasoning for the positive relationship, the author reverts to Merton (1987) and his theory that under-diversified investors demand higher return for high IVOL stocks. Further, the author offers an explanation for the findings of Ang et al. (2006), advocating that mean return reversals of stocks that have high IVOL are the underlying driving force. In other words, the author suggests that stocks that showed temporarily high returns in the previous month will return to towards their mean return, thus earning extremely low returns in the next month.

Huang et al. (2010) follow Fu (2009) and also use an EGARCH model with monthly returns. While they replicate the results of Ang et al. (2006) using realised IVOL, they confirm the positive relationship using EGARCH. The authors also suggest that mean return reversals can act as an explanation for the findings of Ang et al. (2006).

Further studies employing EGARCH models with findings of a positive relationship between IVOL and expected returns are Eiling (2013), Nath and Brooks (2015), Chichernea et al. (2015), and Brockman et al. (2022). Eiling (2013) confirms a positive relationship between expected IVOL and expected returns with significant alphas in the CAPM and FF3 model. She further investigates that industry-idiosyncratic human capital can partly explain the IVOL puzzle. Chichernea et al. (2015) also find a positive relationship between expected IVOL estimated using an EGARCH model and expected returns. The authors further argue that there is an important relationship between IVOL and the investor base of a stock, showing that IVOL premiums are larger for neglected stocks and smaller for well covered stocks. Nath and Brooks (2015) employ a GARCH model specific to Australian data and find conflicting results, concluding that the IVOL puzzle is a model specification problem. Finally, Brockman et al. (2022) show international evidence that the relationship between expected IVOL estimated by EGARCH models and expected returns is significantly positive, in both developed as well as emerging markets. While according to the authors the economic significance varies widely across countries, their findings contradict at least to some extent previously country-specific research on emerging markets, such as Nartea et al. (2010); Aboulamer and Kryzanowski (2016).

Grobys (2014) tries to replicate the study of Ang et al. (2006) on a portfolio level using 52 stock indices in different countries, mimicking a globally aligned investor. The author's findings contradict Ang et al. (2006), as IVOL seems to be positively priced and the zero-cost strategy of going long in high IVOL portfolios and short in low IVOL portfolios earns an excess return of over 1% p.m. irrespective of economic cycle.

2.2.3 Conflicting findings on idiosyncratic volatility

Bali and Cakici (2008) draw inspiration from Ang et al. (2006), but also build upon their research by incorporating different estimation methodologies, weighting schemes, breakpoints, and samples. For daily data from three exchanges (NYSE, AMEX, NASDAQ), the authors find a significant negative relationship for value-weighted portfolios. However, the relationship for value-weighted portfolios turns insignificant when using NYSE breakpoints or forming portfolios with 20% of the market share each. Using daily data from NYSE only, the authors find no significant results, except when looking at FF3 alphas (significant negative relation). The use of monthly data across samples, breakpoints and weighting schemes does not yield significant results for the authors. Finally, the formation of inverse volatility-weighted portfolios does not return significant results either. It is worth noting that Bali and Cakici (2008) carry out a series of robustness tests wherein they exclude small, illiquid, and penny stocks from their analysis. As a result, the findings become statistically insignificant. The authors also examine which estimation methodology (either using daily or monthly data) measures IVOL with greater relative accuracy, and find that the monthly measure prevails. Against this background, the authors conclude that no significant negative trade-off between IVOL and returns can exist, as the monthly measure renders the results to be flat or very weak. Given the aforementioned superiority of estimating IVOL with monthly data, this means that results obtained using the daily estimation methodology should not be used to draw conclusions.

Boehme et al. (2009) measure IVOL as the previous year's standard deviation of weekly excess raw returns against the CRSP VWRETD index. Moreover, their findings show to be robust to other IVOL estimation methodologies. The authors argue that there is a positive relationship between IVOL and expected returns when controlling for visibility and short-sale activity. However, their findings are contradictory, albeit insignificant, as they find a weakly negative relationship for stocks that show high visibility and short-sale activity.

Fink et al. (2012) and Guo et al. (2014) present further conflicting findings as they adjust their EGARCH models for the look-ahead bias which is, as both papers criticise, not accounted for by Fu (2009). More specifically, both papers argue that the EGARCH model, presented in Fu (2009); Huang et al. (2010) and other papers, uses the return in month t to estimate expected IVOL in month t. The implication is intuitive, as high returns in month t can introduce an upward bias on EGARCH estimated expected IVOL in month t. While this effect holds symmetrically in both directions, extreme positive returns are more common than negative returns, resulting in a positively skewed estimate. After controlling for this bias, both Fink et al. (2012) and Guo et al. (2014) find no significant relationship between expected IVOL and expected returns. The criticism is confirmed by Bali et al. (2018) and Park et al. (2020). In a related study, the former only use observations available through month $t-1$ when estimating expected IVOL with an EGARCH model.

Under the assumption that it takes time for innovations in IVOL to be fully priced in, Rachwalski and Wen (2013) distinguish between recent IVOL (last six months), and distant IVOL (six-months lagged). For recent IVOL, the authors find a negative relationship with future returns, but argue that for any stock with a positive price of IVOL, the negative relationship should only be temporary. Indeed the authors find that initially negative returns for zero-cost (i.e. L/S) IVOL portfolios turn consistently positive after six months.

Following the theory of costly arbitrage, Cao and Han (2016) argue that for underpriced (overpriced) stocks there should be a positive (negative) relationship between expected returns and IVOL. The authors use an EGARCH model[11] to estimate idiosyncratic volatility and find evidence in line with their theoretical argumentation. It is worth noting that according to the authors for stocks which are neither under- nor overpriced, IVOL plays no role in determining future returns.

Aslanidis et al. (2018) discuss the influence of macro-finance variables on the IVOL puzzle. For their large sample of macroeconomic and financial predictive variables, the authors use Principal Component Analysis (PCA) to construct one principal component (PC) for each group of predictive variables[12]. After constructing lagged IVOL following Ang et al. (2006), the authors then regress both lagged IVOL and the PCs on the stocks' IVOL at month t. Subsequently, Fama and MacBeth (1973) regressions are run. While the authors' findings without the macro-finance variables are consistent with Ang et al. (2006), the results turn significantly positive when the PCs are included.

[11] Adjusted for the look-ahead bias identified by Fink et al. (2012); Guo et al. (2014); Bali et al. (2018); Park et al. (2020).

[12] Examples for macroeconomic and financial variable categories are employment, housing, interest rates, output, inflation, and stock market.

2.3 Lottery-like pay-out preferences and the MAX effect

2.3.1 Bali, Cakici & Whitelaw's findings on the MAX effect

In addition to the IVOL puzzle, coined by Ang et al. (2006, 2009), Bali et al. (2011) added to the academic debate with their research on the MAX effect. The authors find a significant negative relationship between MAX and future returns, for both equally- and value-weighted decile portfolios. As a robustness test, the authors also expand their estimation methodology from simply using the highest daily return in the preceding month to averaging over the five highest return observations of the last month per stock. Interestingly, this has no remarkable impact on value-weighted portfolios, but improves the significance of results for equally-weighted portfolios.

Using bivariate sorts, the authors find that the MAX effect is robust to controlling for IVOL. In other words, when sorting on IVOL first, and MAX thereafter, the MAX effect persists. Further, when sorting on MAX first and IVOL thereafter, the relationship between IVOL and future returns is reversed. For value-weighted portfolios, the significance is reduced, while for equally-weighted portfolios the relationship turns *positive* and stays significant. Finally, Bali et al. (2011) also examine the MIN effect, which looks at extreme negative daily returns. Here, the authors find the opposite effect to be true, albeit insignificant, with investors usually undervaluing high MIN stocks.

Bali et al. (2011) explain the phenomenon with investors' preferences for skewness. They argue that investors dislike IVOL, but want to invest in stocks that potentially have abnormally high returns, i.e. lottery-like pay-outs. This drives up the stocks' prices and hence reduces future returns.

2.3.2 Further research on the MAX effect

Annaert et al. (2013), and Walkshäusl (2014) confirm the findings of Bali et al. (2011) with European data. The former paper analyses data from 13 European countries, while Walkshäusl (2014) limits his sample to countries that belong to the European Monetary Union. That said, both papers not only find that high MAX stocks correlate negatively with future returns, but also that the puzzling IVOL relationship weakens when first controlling for MAX. Chan and Chui (2016) confirm the effect for the Hong Kong stock exchange. Moreover, the authors observe that the MAX premium is more pronounced in periods of lower overall returns, which points to investors' heightened inclination towards lottery-like pay-outs during bad times. A similar finding is presented by Cheon and Lee (2018), who show that in the Korean equity market, which is largely dominated by retail investors who are more susceptible to behavioural biases, high MAX stocks are overpriced. This finding is even more apparent during times of high market volatility. Zhong and Gray (2016) show supporting evidence for an Australian sample spanning from from 1991−2013.

Bali et al. (2011) also earned criticism for the aforementioned paper. Chen and Petkova (2012) show that the MAX effect does not hold significant when excluding penny stocks from their data, and Hou and Loh (2016), who are able to confirm the sign reversal when controlling for MAX, view the findings as unsurprising for two reasons. Firstly, they reiterate the strong correlation between the IVOL and MAX[13]. Secondly, they argue that the findings of Bali et al. (2011) simply depict a mechanical relationship, since the MAX estimation is a range-based measure of volatility.

[13]The authors confirm a correlation of about 0.90 between the two measures, in line with our findings reported in Table 13.

3 Methodology and Data

3.1 Methodology

3.1.1 Return definition

In this paper, returns r_t^i of security i at time t are calculated as simple returns using the daily closing bid price:

$$r_t^i = \frac{p_t^i \frac{df_t^i}{sf_t^i}}{p_{t-1}^i \frac{df_{t-1}^i}{sf_{t-1}^i}} - 1 \tag{1}$$

where p_t^i is the closing bid price of security i at time t, df_t^i is the dividend adjustment factor of security i at time t, and sf_t^i is the stock split adjustment factor of security i at time t[14]. The same principle is followed for the calculation of monthly returns, which are calculated from the first full month of available data to the first day of the next full month of available data, meaning that a delisting in month t would result in the data ending in month $t-1$. Due to the existence of multiple currencies across European countries as well as the adoption of the Euro in 1999, all prices are converted into USD before returns are calculated.

3.1.2 Total and idiosyncratic volatility

First, total volatility is measured on a per-stock basis. Total volatility is simply defined as $\sqrt{var(r_t^i)}$. In line with Ang et al. (2006), daily stock returns are regressed on the Fama-French three-factor model to obtain the residuals (Fama and French, 1993):

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \tag{2}$$

where idiosyncratic volatility is measured relative to the Fama-French three-factor model as $\sqrt{var(\varepsilon_t^i)}$.

[14] Dividend and stock split adjustment factors are provided by Compustat Global.

3.1.3 Portfolio formation

Following Ang et al.'s (2006) $L/M/N$ portfolio formation approach, we define an estimation period of L months, a waiting period of M months, and a holding period of N months. At month t, we compute total and idiosyncratic volatilities by regressing daily data for each stock on Equation (2). This estimation is done over a window from $t - L - M$ to $t - M$. The results are then stored for M months, and quintile portfolios are formed with portfolio 1 (5) representing the lowest (highest) total or idiosyncratic volatility, respectively. Portfolios are formed both on a value-weighted and equally-weighted basis. After a holding period of N months, starting at month t, we report the quintile portfolios' returns.

The base case scenario employs a 1/0/1 strategy, resulting in the rebalancing of portfolios each month based on the previous month's volatility estimations without a waiting period. That said, other $L/M/N$ strategies are employed to test for the findings' robustness[15]. Consistent with Ang et al. (2006), we adopt Jegadeesh and Titman's (1993)[16] approach for portfolios featuring $L > 1$ and $N > 1$, in that quintile portfolios for each of the L months of estimation are formed individually. The aggregate quintile portfolios are then formed by taking the simple average of the N portfolios per quintile formed during the estimation window, meaning that quintile portfolio 1 (5) consists to $1/N^{th}$ of each of the N estimation periods' lowest (highest) total or idiosyncratic volatility portfolios. For example, in our 12/1/12 strategy at the beginning of each month, the individual quintile portfolio ($1/12^{th}$ of the aggregate quintile portfolio) from the oldest estimation period, $t - 13$, is replaced by the individual quintile portfolio from the most recent estimation period. The quintile return of any given month is calculated as a simple mean of the 12 portfolios created over the past 12 months. The described process is identical for the formation of portfolios sorted by maximum daily returns.

Finally, controls are implemented in the form of double-sorts, resulting in 25 individual portfolios. Subsequently averaging over the quintile portfolios introduced by the control variable allows us to obtain five portfolios with similar levels of the control variable, while

[15] See Section 4.1.2.

[16] In their seminal paper on what would later become known as the momentum factor, the two authors employ portfolio sorts over 3-12 month periods (Jegadeesh and Titman, 1993).

the levels of the variable of interest are increasing with the quintiles. We control for MAX, Size, and Momentum (see Section 4.2.2).

3.1.4 Adjustments for incomplete observations

It is important to note that in our data set, smaller stocks tend to have worse data quality and, thus, are excluded more often due to many missing observations, inconsistent returns or readjustment factors. In order to deal with this issue, we follow the volatility calculation methodology of Zhang et al. (2021), where observations with data for less than 50% of the trading days are excluded. Ang et al. (2009), working with European data, treat this issue by excluding the bottom 5% of market capitalisation. Nevertheless, in this paper we keep all observations except for firms in the lowest trading volume percentile in each month in order to avoid confounding a lack of trading data with low volatility. We later include the 5% threshold as robustness check for our results in section 4.2.3.

Moreover, due to the requirement of available data for at least 50% of the total number of trading days, companies that got listed late in the estimation period or delisted early in the estimation period are not included in the portfolio sorting for the next holding period. Finally, if a company is delisted during the holding period we assign a weight of zero in the average return calculation of its quintile portfolio.

3.1.5 Newey-West lag

To account for heteroskedasticity and autocorrelation, we use Newey and West (1987) adjusted standard errors. Following Bali et al. (2016) and Newey and West (1987), the optimal lag m for the Newey-West adjusted standard error is

$$m = 4(T/100)^{2/9} \tag{3}$$

where T is the number of periods, i.e. months, in the time series. Given the data examined in this paper spans from 1993 to 2022, the resulting lag m used in the Newey-West adjusted standard errors ≈ 5.

3.2 Data

3.2.1 Sample construction

The main data set used for the analysis in this paper was derived from the Compustat Global Security Daily database from S&P Global Market Intelligence (2023). The time period of data used in this paper spans from December 1, 1993 to December 31, 2022 (i.e. 382 months). Moreover, we limit our analysis to 15 developed European countries, as listed in Table 1. We distinguish European and non-European companies by the location filters, stock exchange filters and currencies. In the European-level analysis we include companies that list in another European jurisdiction than its headquarters' location and/or in another currency. When we conduct the country-level analysis, we include only companies that are listed on a local stock exchange and are denominated in the national currency (Euro or the pre-Euro national currency, excluding Denmark, Norway, Switzerland, Sweden and the United Kingdom)[17].

3.2.2 Sample description

The United Kingdom, Germany and France represent more than half of the European stock market capitalisation, with a share of 25.7%, 16.8% and 13.1%, respectively (i.e. 55.6% of the total market). These countries influence both value-weighted and equally-weighted European level results substantially. While the top three countries also show the highest total and average number of companies, those numbers are not necessarily related to the countries' market share. For example, Switzerland has a relatively small number of listed stocks that represent only 3.6% of European companies over the period but given their large market capitalisation, Swiss companies represent as much as 10.5% of the total European market.

The mean monthly return of all companies in the sample is 0.80% during the period of analysis (i.e., $\approx$ 10% p.a.). However, it is important to note that this average is driven by the increase in the number of companies in more recent years as shown in Figure 1.

[17]For example, an Italian company that is listed in the UK as a GBP-denominated stock would be included in the European level analysis, but excluded from the results for Italy.

Table 1: Summary statistics

The table shows country-level summary statistics for each of the developed markets in our sample, as well as aggregate statistics on European level. We show the total and average number of companies per country, as well as the share of European total market capitalisation. Finally, the table reports mean monthly returns with respective standard deviations in percent per country.

Country	Total number of companies		Average number of companies		Market share	Monthly returns	
	Number	Share	Number	Share	(In %)	Mean	St. Dev.
AUT	167	1.2%	64	1.6%	0.9%	0.98%	16.1%
BEL	303	2.3%	114	2.8%	3.0%	0.82%	12.3%
CHE	480	3.6%	176	4.4%	10.5%	0.86%	13.9%
DEU	1596	11.9%	569	14.1%	16.8%	0.82%	21.3%
DNK	393	2.9%	136	3.4%	1.5%	0.77%	14.6%
ESP	437	3.2%	131	3.2%	6.8%	0.91%	13.1%
FIN	304	2.3%	110	2.7%	1.7%	0.95%	13.2%
FRA	1771	13.2%	572	14.2%	13.1%	0.89%	16.2%
GBR	4554	33.8%	1211	30.0%	25.7%	0.72%	18.5%
IRL	138	1.0%	41	1.0%	2.1%	1.04%	18.5%
ITA	805	6.0%	251	6.2%	6.3%	0.49%	13.7%
NLD	375	2.8%	128	3.2%	5.0%	0.84%	14.5%
NOR	622	4.6%	146	3.6%	2.0%	0.98%	18.0%
PRT	126	0.9%	47	1.2%	0.8%	0.95%	14.4%
SWE	1385	10.3%	338	8.4%	3.6%	0.86%	19.7%
Europe	13456	100%	4034	100%	100%	0.80%	17.5%

Following a strong increase starting in 1995, the highest number of companies per month in the sample is recorded just before the Global Financial Crisis, before levelling out between 4000 and 4500 throughout the remaining sample period. The data set includes both active companies and delisted stocks, ensuring no survivorship bias.

Stocks in our sample are denominated in 17 different currencies including the currencies that ceased to exist after the adoption of the Euro. We also maintain USD-denominated stocks that are listed by European companies on an European exchange[18]. For comparability, we convert all prices into USD prior to computing daily and monthly returns. Data from S&P Global Market Intelligence (2023), the Bank of England (2023) and the Federal Reserve (2023) is used for daily cross-currency exchange rates. Table 2 depicts

[18]However, stocks denominated in USD are excluded from the country-level analysis in Section 4.4.

Figure 1: Number of companies in the sample over time

We show the development of the number of companies in our data sample over time. The current level of approximately 4000 observations in each month is reached around the year 2000. The x-axis denotes the time period, the y-axis denotes the number of companies.

the composition of stocks' currency denomination in each country. During the period of analysis, only 43.7% of monthly observations of European stock prices are denominated in Euro. The conversion to USD also facilitates the use of European FF3 factors published by Kenneth R. French, which are USD-denominated and apply the U.S. one-month treasury bill as risk-free rate.

3.2.3 Fama-French factor data and risk-free rate

Following Ang et al. (2006), we regress our stock returns against the Fama-French three-factor model to measure idiosyncratic volatility. Working on a European level allows for the use of Fama and French's publicly available three factor data[19] set for Europe. The factor data for Europe covers the same countries represented, and examined, in the European stock data from Compustat Global (see Table 1). This regional factor data set is sufficient for regressing country-specific stocks, as a large share of country specific factors within

[19]See French (2022) for the data set.

one region can in fact be explained by regional factors (Brooks and Del Negro, 2005)[20]. To measure the quintile portfolios' performance relative to established factor models such as the CAPM, the FF3, and the FF5, we use monthly factor data from Kenneth R. French's website. In both data sets the risk-free rate is defined as the U.S. one-month treasury bill.

Table 2: Currency composition across countries

The table reports the currency composition of each developed market in our sample. Local Cur. describes the respective local currency in countries not part of the European Currency Union (or currencies prior to joining the union). Other describes European currencies that are neither the local currency nor other key currencies listed in the table (e.g. stocks in Sweden denominated in Danish Crowns). Finally, the table describes the aggregate currency composition on European level.

Country	EUR	GBP	USD	CHF	SEK	Local Cur.	Other
AUT	98.6%			1.4%			
BEL	89.5%	0.1%	0.4%			9.8%	0.1%
CHE	5.1%	0.4%	0.9%	92.7%	0.7%		0.3%
DEU	94.5%	0.1%		0.1%		5.4%	
DNK					0.9%	97.8%	1.2%
ESP	82.5%	0.8%				16.7%	
FIN	86.8%	0.7%			1.6%	10.9%	
FRA	86.2%					13.8%	
GBR	0.6%	99%	0.1%		0.1%		0.2%
IRL	64.8%	32%	0.6%	1.3%	0.7%	0.3%	0.3%
ITA	87.1%	0.2%		0.4%		12.4%	
NLD	75.3%	1.1%	1.1%	0.3%	0.3%	21.5%	0.3%
NOR	0.1%	0.1%			0.2%	99.7%	
PRT	87.3%					12.7%	
SWE	0.2%	0.1%			99.3%		0.4%
Europe	43.7%	31.3%	0.1%	4%	8.5%	12.4%	

[20]For example, Brooks and Del Negro (2005) show that an investor diversifying her portfolio across countries within a region can already reduce risk by 50% compared to global diversification.

4 Empirical findings and results discussion

The following section will present and discuss our findings. The 1/0/1 strategy is our base case. Further, additional strategies and the impact of several robustness tests will be analysed. We also dedicate a section to the comparison between the IVOL puzzle and the MAX effect. Finally, the limitations of our research are discussed.

4.1 Results

4.1.1 1/0/1 Strategy

Ang et al. (2006, 2009) employ an $L/M/N$ portfolio formation approach and base their main findings of the relationship between IVOL and returns on the 1/0/1 strategy. The previous month's stock-level IVOL data is used to form quintile portfolios. Since $M = 0$, there is no waiting period, and the subsequent month's portfolio returns are used to draw the relevant conclusions. To counter criticism that the relationship is driven by the effect of microcaps and penny stocks, the authors construct both value- and equally-weighted portfolios. Further robustness tests are also conducted, which we replicate in this paper.

Table 3 reports value-weighted results for the three sorting methodologies TVOL, IVOL, and MAX. It is worth noting that from portfolio 1 to 5 for each strategy, the proportion of market share shows a strictly monotone decrease. This is in line with the findings in Ang et al. (2006, 2009) and shows that smaller stocks are more volatile. An exception is the MAX strategy, where the second quintile represents the largest share of market capitalisation, with quintiles 3 to 5 showing the same trend as TVOL & IVOL.

Panel A, Table 3 shows portfolios sorted by total volatility. The quintile portfolios' returns are decreasing with TVOL, with the zero-cost strategy showing a difference in average monthly returns of -0.61%. This strategy is not priced in neither the CAPM nor the FF3 model, as the zero-cost strategy's alphas are -1.19% and -1.16%, respectively. Both those measures are highly significant at the 0.1% level, with t-statistics of -3.49 and -3.77, respectively. The FF5 model reduces the difference's statistical significance due to the introduction of further factors, capturing the relationship to a larger extent. Panel

Table 3: Value-weighted Portfolios under the 1/0/1 Strategy

We show results for the aggregate European value-weighted portfolios based on three sorting methodologies. Mean and Std. Dev. describe mean monthly raw return and the standard deviation measured in monthly percentage terms. Market Share describes the share of the market captured by each quintile portfolio. Alphas are measured with respect to CAPM, FF3, and FF5. "5-1" describes the zero-cost strategy. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Rank	Mean	Std. Dev.	Market Share	Alphas		
				CAPM	FF3	FF5
Panel A: Portfolios Sorted by Total Volatility						
1	0.76	4.25	35.54%	0.19	0.19	0.01
				[1.89]	[1.88]	[0.05]
2	0.77	5.25	30.91%	0.10	0.08	-0.06
				[1.28]	[1.23]	[-0.67]
3	0.72	6.14	19.62%	-0.05	-0.07	-0.09
				[-0.63]	[-0.78]	[-0.92]
4	0.63	7.47	10.65%	-0.24	-0.23	0.03
				[-1.60]	[-1.63]	[0.16]
5	0.15	9.39	3.28%	-0.81	-0.79	-0.36
				[-2.93]	[-3.15]	[-1.14]
5-1	-0.61	7.38		-1.19	-1.16	-0.54
	[-1.43]			[-3.49]	[-3.77]	[-1.45]
Panel B: Portfolios Sorted by Idiosyncratic Volatility Relative to FF-3						
1	0.80	4.87	48.93%	0.16	0.17	0.03
				[1.79]	[2.13]	[0.36]
2	0.73	5.70	27.09%	0.01	-0.01	-0.08
				[0.08]	[-0.12]	[-0.87]
3	0.73	6.29	14.66%	-0.05	-0.06	-0.05
				[-0.54]	[-0.71]	[-0.48]
4	0.60	7.20	7.01%	-0.25	-0.25	-0.02
				[-1.72]	[-1.86]	[-0.10]
5	0.05	8.93	2.31%	-0.85	-0.84	-0.41
				[-2.85]	[-3.10]	[-1.3]
5-1	-0.74	6.68		-1.19	-1.19	-0.62
	[-1.83]			[-3.44]	[-3.94]	[-1.73]

B, Table 3 shows our results for portfolios sorted on IVOL. The highest IVOL quintile captures 2.31% of the market share, and earns an average monthly raw return of just 0.05%, resulting in a difference of -0.74% between the highest and lowest IVOL quintile portfolio. It is worth noting the material drop in average monthly returns as we move

Table 3 (continued)

Panel C: Portfolios Sorted by Maximum Daily Returns						
1	0.82	4.47	30.74%	0.23	0.23	0.04
				[2.25]	[2.33]	[0.40]
2	0.77	5.23	31.07%	0.09	0.09	-0.01
				[1.23]	[1.22]	[-0.15]
3	0.69	5.83	21.57%	-0.05	-0.05	-0.09
				[-0.69]	[-0.66]	[-0.97]
4	0.59	6.92	12.32%	-0.24	-0.22	-0.08
				[-1.89]	[-1.87]	[-0.57]
5	0.50	8.54	4.31%	-0.41	-0.36	-0.01
				[-1.69]	[-1.66]	[-0.05]
5-1	-0.32	6.29		-0.83	-0.77	-0.23
	[-0.84]			[-2.71]	[-2.94]	[-0.74]

from the fourth to the fifth quintile. Similar to total volatility, traditional factor models cannot capture the relationship, with the long/short strategy's alpha being -1.19% for both the CAPM and FF3. Panel C, Table 3 shows that portfolios sorted by Maximum Daily Returns exhibit the smallest difference of -0.32% between extreme quintiles, with the highest MAX quintile still earning monthly average raw returns of 0.50%. That said, the significance of a negative alpha for the long/short strategy persists, with a CAPM and FF3-alpha of -0.83% and -0.77%, respectively. Both are significant at the 5% level.

Table 4 shows the same results as Table 3, but with equally-weighted portfolios. Panel A, Table 4 shows portfolios sorted by TVOL, which are largely unchanged to the results from Panel A, Table 3. The difference in raw returns between quintile portfolios 1 and 5 is now -0.54% (VW: -0.61%), and both the CAPM and FF3 alphas of the zero-cost strategy stay significant at the 0.1% level. Panel B, Table 4 shows the results for equally-weighted portfolios sorted by IVOL, which are in line with Ang et al. (2009) and Bali and Cakici (2008). Using U.S. data, the latter report more significant results for value-weighted portfolios sorted by IVOL compared to equally-weighted. The former also succeed to show this relation to persist in international markets[21]. In our case, the t-statistic for the difference in mean return for the zero-cost strategy in Panel B, Table 4, decreases in

[21] Ang et al. (2009) use value-weighted Fama-MacBeth regressions.

Table 4: Equally-weighted Portfolios under the 1/0/1 Strategy

We show results for equally-weighted portfolios based on three sorting methodologies. Mean and Std. Dev. describe mean monthly raw return and the standard deviation measured in monthly percentage terms. Alphas are measured with respect to CAPM, FF3, and FF5. "5-1" describes the zero-cost strategy. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Rank	Mean	Std. Dev.	Alphas		
			CAPM	FF3	FF5
Panel A: Portfolios Sorted by Total Volatility					
1	0.87	4.41	0.27	0.17	0.09
			[2.34]	[2.38]	[1.13]
2	0.94	5.30	0.25	0.15	0.10
			[2.27]	[2.10]	[1.25]
3	0.94	5.91	0.19	0.09	0.16
			[1.60]	[1.22]	[1.85]
4	0.71	6.74	-0.10	-0.18	0.08
			[-0.58]	[-1.48]	[0.63]
5	0.33	7.92	-0.51	-0.57	-0.05
			[-1.69]	[-2.50]	[-0.23]
5-1	-0.54	5.10	-0.96	-0.92	-0.32
	[-1.46]		[-3.17]	[-3.7]	[-1.23]
Panel B: Portfolios Sorted by Idiosyncratic Volatility Relative to FF-3					
1	0.88	4.61	0.26	0.17	0.07
			[2.46]	[2.49]	[1.02]
2	0.99	5.41	0.28	0.18	0.13
			[2.61]	[2.66]	[1.79]
3	0.92	5.93	0.16	0.06	0.14
			[1.32]	[0.81]	[1.65]
4	0.68	6.56	-0.11	-0.19	0.06
			[-0.64]	[-1.63]	[0.47]
5	0.33	7.74	-0.49	-0.56	-0.04
			[-1.63]	[-2.44]	[-0.17]
5-1	-0.55	4.88	-0.93	-0.90	-0.29
	[-1.52]		[-3.08]	[-3.66]	[-1.14]

significance to -1.52 compared to -1.83 in Panel B, Table 3. A slight decrease in significance levels for the zero-cost strategy's alphas with respect to the CAPM and FF3 can also be observed. Interestingly, Panel C, Table 4 goes against this observation. In contrast to Bali et al. (2011), equally-weighted portfolios sorted by maximum daily returns appear to yield statistically superior results compared to the value-weighted portfolios[22].

[22]Note that Bali et al. (2011) use decile portfolio sorts instead of quintiles, which has a strong impact

Table 4 (continued)

Panel C: Portfolios Sorted by Maximum Daily Returns					
1	0.83	4.74	0.20	0.09	0.06
			[1.71]	[1.29]	[0.75]
2	0.94	5.38	0.23	0.13	0.12
			[2.10]	[1.91]	[1.58]
3	0.89	5.88	0.15	0.05	0.12
			[1.19]	[0.65]	[1.31]
4	0.71	6.5	-0.08	-0.16	0.06
			[-0.51]	[-1.47]	[0.51]
5	0.43	7.58	-0.40	-0.46	0.01
			[-1.40]	[-2.17]	[0.03]
5-1	-0.40	4.34	-0.77	-0.73	-0.23
	[-1.24]		[-2.88]	[-3.25]	[-1.00]

Table 5 shows detailed regression results for all six zero-cost strategies under the 1/0/1 formation strategy. As can be seen in the detailed results in Tables 3 & 4, all alphas are significant at the 0.1% level except for the MAX VW strategy's, which is significant at the 1% level. Across strategies, positive loadings on the MKT factor significant at the 0.1% level suggest a positively correlated systematic risk exposure to the market. For the SMB factor, the results are the most ambiguous. While all six strategies show positive loadings, suggesting a tilt towards small stocks in the portfolios, the results are less significant for the TVOL VW strategy, and even insignificant for the MAX VW strategy.

For the HML factor, we observe highly significant negative loadings across the strategies, which indicates a tilt towards companies with low book values relative to their current market values. Companies with low book values relative to their market values are expected to grow in the future, thus are often labelled growth stocks. Adjusted R^2 values range from 0.21 to 0.32. Overall, the results indicate that the portfolios sorted on IVOL, TVOL, and MAX have a higher proportion of small cap stocks and growth stocks, respectively.

Finally, Figure 2 shows the cumulative returns of all strategies' portfolios 1 and 5 over the entire sample period. Subfigures 2a), 2c), and 2e) depict equally-weighted strategies,

on their extreme deciles' return characteristics.

Table 5: Detailed regression results for the 5-1 strategies

We show detailed FF3-regression outputs for the 1/0/1 strategy based on different sorting methodologies. Alpha describes the constant, MKT describes the excess return of the Market, SMB describes the return of portfolios with firms of small market capitalisation minus the return of portfolios with firms of large market capitalisation, HML describes the return of portfolios with firms that show high book-to-market ratios minus the return of portfolios with firms that show low book-to-market ratios. EW describes equally-weighted portfolios, VW describes value-weighted portfolios. Robust Newey-West (1987) standard errors are reported in brackets. Further, R^2 and Adjusted R^2 values are reported. Significance levels are denominated by up to three stars, with the corresponding p-values given below the table.

	IVOL		TVOL		MAX	
	EW	VW	EW	VW	EW	VW
Alpha	-0.90^{***}	-1.19^{***}	-0.92^{***}	-1.16^{***}	-0.73^{***}	-0.77^{**}
	(0.22)	(0.32)	(0.23)	(0.34)	(0.20)	(0.29)
MKT	0.45^{***}	0.57^{***}	0.53^{***}	0.81^{***}	0.43^{***}	0.67^{***}
	(0.04)	(0.06)	(0.05)	(0.07)	(0.04)	(0.06)
SMB	0.58^{***}	0.65^{***}	0.50^{***}	0.36^{*}	0.42^{***}	0.27
	(0.10)	(0.15)	(0.11)	(0.16)	(0.09)	(0.14)
HML	-0.49^{***}	-0.38^{**}	-0.50^{***}	-0.34^{**}	-0.45^{***}	-0.43^{***}
	(0.08)	(0.12)	(0.08)	(0.12)	(0.07)	(0.11)
R^2	0.29	0.21	0.32	0.30	0.30	0.29
Adj. R^2	0.29	0.21	0.32	0.29	0.30	0.28

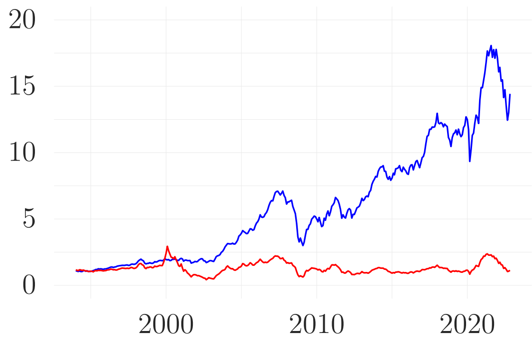
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

whereas Subfigures 2b), 2d), and 2f) show value-weighted strategies. It is worth noting that the cumulative returns for the lowest quintile of the value-weighted portfolios appear to be smaller than the equally weighted portfolios' across strategies. This is particularly pronounced for the TVOL strategy, which fares the worst. Until the year 2000, both quintile portfolios achieve similar cumulative returns across strategies. After 2000, quintile portfolios 5 go through a period of continuous negative returns, whereas the positive returns of quintile portfolios 1 cause a growing spread. Negative return impacts of the global financial crisis around $2008 - 2009$, as well as the Covid-19 pandemic around the year 2020 are clearly visible across all six graphs.

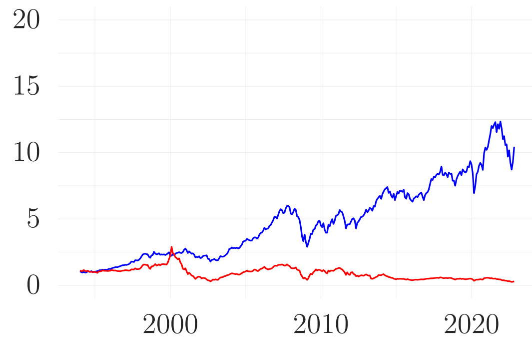
Figure 2: Cumulative returns across strategies

We show cumulative returns for each of the six strategies, over the period from 1993 - 2022. The graphs are sorted by strategy over rows and by weighting methodology over columns. Portfolio 5 is depicted as a red line, portfolio 1 is depicted as a blue line. The y-axis denotes cumulative raw returns in %.

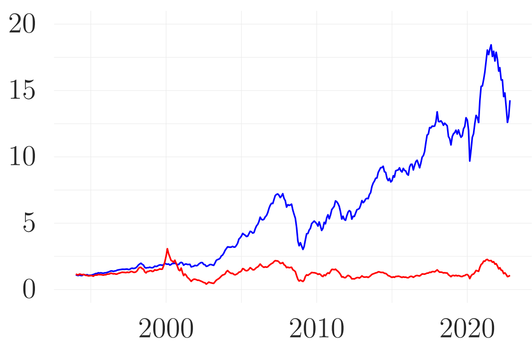
Equally-weighted portfolios	Value-weighted portfolios



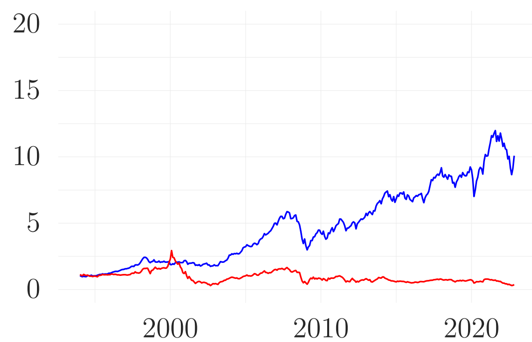
(a) IVOL EW



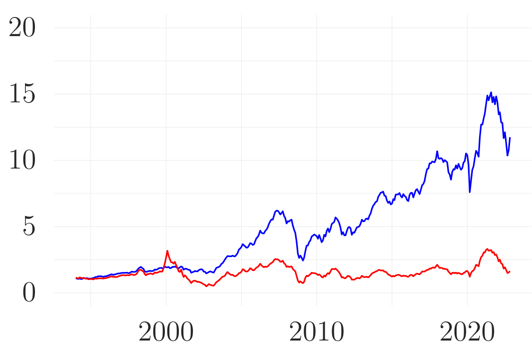
(b) IVOL VW



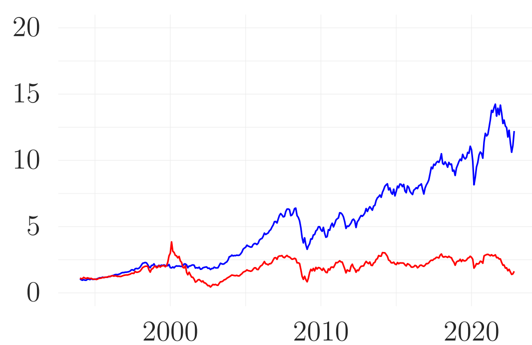
(c) TVOL EW



(d) TVOL VW



(e) MAX EW



(f) MAX VW

4.1.2 Additional L/M/N Strategies

The choice to use 1/0/1 strategy is based on academic literature on volatility and MAX pricing anomalies, as well as the two reference papers (Ang et al. (2006) and Bali et al. (2011)). That said, there has been criticism with regards to the 1/0/1 strategy as it is argued that the resulting estimates are driven by short-term events. Therefore, we implement additional L/M/N strategies to verify if our results remain significant under different specifications.

Indeed, longer estimation and holding periods not only confirm our findings but in some instances provide even more statistically significant results, as can be seen in Tables 6, 7 & 8. This effect is particularly strong with regards to the MAX anomaly for which the

Table 6: IVOL portfolios under different trading strategies

We show results for portfolios sorted by idiosyncratic volatility with additional estimation, waiting, and holding periods. The columns describing portfolio quintiles and the zero-cost strategy ("5-1") show mean monthly raw returns. Alphas are measured with respect to the Fama and French (1993) three-factor model. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Strategy	First	Second	Third	Fourth	Fifth	5-1	FF3 alpha
Panel A: Value-weighted portfolios Sorted by Idiosyncratic Volatility Relative to FF-3							
3/0/1	0.74	0.86	0.68	0.45	-0.05	-0.79	-1.22
						[-1.62]	[-3.30]
6/0/1	0.72	0.86	0.71	0.47	-0.18	-0.90	-1.37
						[-1.94]	[-4.16]
3/1/12	0.94	0.80	0.61	0.37	0.07	-0.87	-0.70
						[-2.01]	[-3.03]
12/1/12	0.78	0.77	0.74	0.44	-0.13	-0.90	-0.95
						[-1.65]	[-6.58]
Panel B: Equally-weighted portfolios Sorted by Idiosyncratic Volatility Relative to FF-3							
3/0/1	0.90	0.97	0.91	0.62	0.21	-0.69	-1.03
						[-1.73]	[-3.94]
6/0/1	0.86	0.96	0.84	0.57	0.21	-0.66	-1.00
						[-1.60]	[-3.84]
3/1/12	0.82	0.88	0.79	0.54	0.36	-0.46	-0.77
						[-1.15]	[-5.66]
12/1/12	0.82	0.90	0.83	0.53	0.42	-0.40	-0.71
						[-0.89]	[-4.91]

Table 7: TVOL portfolios under different trading strategies

We show results for portfolios sorted by total volatility with additional estimation, waiting, and holding periods. The columns describing portfolio quintiles and the zero-cost strategy ("5-1") show mean monthly raw returns. Alphas are measured with respect to the Fama and French (1993) three-factor model. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Strategy	First	Second	Third	Fourth	Fifth	5-1	FF3 alpha
Panel A: Value-weighted portfolios Sorted by Total Volatility							
3/0/1	0.75	0.77	0.71	0.52	-0.01	-0.76	-1.31
						[-1.53]	[-3.82]
6/0/1	0.76	0.75	0.66	0.53	0.00	-0.76	-1.37
						[-1.49]	[-4.04]
3/1/12	0.81	0.80	0.66	0.45	0.17	-0.64	-0.69
						[-1.87]	[-3.33]
12/1/12	0.72	0.77	0.77	0.38	0.14	-0.57	-0.77
						[-1.18]	[-3.06]
Panel B: Equally-weighted portfolios Sorted by Total Volatility							
3/0/1	0.89	0.96	0.89	0.67	0.20	-0.69	-1.07
						[-1.68]	[-4.04]
6/0/1	0.87	0.94	0.84	0.59	0.20	-0.67	-1.05
						[-1.59]	[-3.92]
3/1/12	0.83	0.87	0.78	0.55	0.36	-0.47	-0.82
						[-1.13]	[-5.80]
12/1/12	0.83	0.89	0.81	0.57	0.41	-0.42	-0.77
						[-0.89]	[-5.12]

1/0/1 strategy with quintiles did not yield unequivocal results for the zero-cost portfolio. Employing a 3/1/12 trading strategy, the t-statistic improves to -2.89 (Panel A, Table 8) for the value-weighted portfolio, compared to the equivalent t-statistic of -0.84 in the 1/0/1 specification. Overall, there is no clear relationship between longer estimation or holding periods and more significant results.

It is important to note that we adjust the raw returns' t-statistics for heteroskedasticity and autocorrelation following Newey and West (1987). This adjustment is necessary due to the fact that under our 12 month holding period we hold the 12 portfolios formed each month over the previous 12 months and calculate monthly returns as a simple average of those 12 portfolios. While this mitigates the impact of outlier months, the autocorrelation

Table 8: MAX portfolios under different trading strategies

We show results for portfolios sorted by maximum daily returns within a month, with additional estimation, waiting, and holding periods. The columns describing portfolio quintiles and the zero-cost strategy ("5-1") show mean monthly raw returns. Alphas are measured with respect to the Fama and French (1993) three-factor model. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Strategy	First	Second	Third	Fourth	Fifth	5-1	FF3 alpha
Panel A: Value-weighted portfolios Sorted by Maximum Daily Returns							
3/0/1	0.77	0.70	0.67	0.52	0.45	-0.32	-0.79
						[-0.82]	[-2.91]
6/0/1	0.75	0.72	0.63	0.53	0.41	-0.34	-0.77
						[-0.91]	[-2.86]
3/1/12	1.01	0.77	0.63	0.42	0.10	-0.91	-0.76
						[-2.89]	[-4.17]
12/1/12	0.89	0.86	0.66	0.40	0.29	-0.61	-0.57
						[-1.57]	[-2.57]
Panel B: Equally-weighted portfolios Sorted by Maximum Daily Returns							
3/0/1	0.83	0.89	0.82	0.68	0.38	-0.44	-0.79
						[-1.25]	[-3.37]
6/0/1	0.80	0.85	0.81	0.65	0.33	-0.47	-0.81
						[-1.27]	[-3.37]
3/1/12	0.78	0.83	0.76	0.60	0.43	-0.35	-0.66
						[-1.04]	[-5.40]
12/1/12	0.82	0.88	0.78	0.55	0.47	-0.34	-0.65
						[-0.87]	[-4.95]

between one month's returns and the next is significantly higher than in the 1/0/1 specification because we change only $1/12^{th}$ of the portfolio each month. That said, the IVOL and MAX anomalies persist as controlling for heteroskedasticity and autocorrelation does not materially change the FF3 alphas' significance.

Alternative specifications of the long/short strategy based on IVOL yield a statistical significance similar to that of 1/0/1 specification. At the same time, Panel A, Table 6 shows that the differences in returns between the highest and lowest IVOL value-weighted portfolios increase compared to the original specification (Panel B, Table 3: -0.74%). This is primarily driven by the abysmally low returns of the high IVOL quintiles in Panel A, Table 6. In the 6/0/1 specification, the average monthly return of the fifth portfolio is -

0.18%. However, such small returns only apply to value-weighted and not equally-weighted portfolios. For the IVOL strategy, equally-weighted zero-cost portfolios across all trading strategies do not pass the 5% significance level (however, some strategies are significant at 10% (see Panel B, Table 6). Finally, all *L/M/N* specifications across the three sorting methodologies yield significant FF3 alphas.

The results of portfolios ranked by TVOL follow a similar pattern to those ranked by IVOL, with the only key difference being that the magnitude of the long/short average returns as well as FF3 alphas are smaller when TVOL is used as a ranking criterion for the value-weighted portfolios.

4.2 Controls and robustness tests

The results of the 1/0/1 quintile portfolio strategy can be criticised in several ways. To counter criticism and check for robustness, we conduct a number of tests. Next to the choice of different parameters for the estimation, waiting, and holding periods, quintile breakpoints will be complemented by decile breakpoints. Further, tests of different sub-samples try to confirm the IVOL puzzle's persistence over time. Moreover, the robustness of different MAX specifications will be studied. Finally, firm-specific characteristics will be controlled for in more detail.

4.2.1 Decile portfolios

In the academic literature on market anomalies, authors employ various ranking methodologies. Ang et al. (2006) opt to sort stocks into five different portfolios, while Bali and Cakici (2008) use ten portfolios. To check the sensitivity of the results to the number of breakpoints, we rerun our analysis using decile instead of quintile portfolios for both the 1/0/1 and 12/1/12 strategies. The results are shown in Table 9.

When using decile value-weighted portfolios, the long/short strategy yields statistically significant negative returns with t-statistics that are slightly larger in absolute value than in the original specification using quintile portfolios. The most striking difference between decile and quintile specification results can be seen in the TVOL specification. Using five

Table 9: Decile portfolios under the 1/0/1 and 12/1/12 strategy

We show results for both value- and equally-weighted decile portfolios sorted on idiosyncratic volatility, total volatility, and maximum daily returns. Panel A shows results for the 1/0/1 strategy, Panel B shows results for the 12/1/12 strategy. The rows describing extreme deciles and the zero-cost strategy ("10-1") show mean monthly raw returns. Alphas are measured with respect to the Fama and French (1993) three-factor model. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

	IVOL		TVOL		MAX	
	EW	VW	EW	VW	EW	VW
Panel A: 1/0/1						
1	0.82%	0.83%	0.79%	0.76%	0.72%	0.92%
10	0.17%	-0.07%	0.14%	-0.48%	0.27%	0.49%
10-1	-0.65%	-0.89%	-0.66%	-1.24%	-0.45%	-0.42%
	[-1.47]	[-1.57]	[-1.48]	[-2.12]	[-1.20]	[-0.90]
FF3 alpha	-1.04%	-1.37%	-1.08%	-1.82%	-0.80%	-0.94%
	[-3.40]	[-2.82]	[-3.55]	[-4.00]	[-2.92]	[-2.62]
Panel B: 12/1/12						
1	0.76%	0.83%	0.78%	0.83%	0.78%	0.97%
10	0.56%	-0.24%	0.53%	-0.23%	0.54%	0.31%
10-1	-0.20%	-1.06%	-0.26%	-1.05%	-0.24%	-0.66%
	[-0.39]	[-1.55]	[-0.49]	[-1.62]	[-0.52]	[-1.39]
FF3 alpha	-0.53%	-1.15%	-0.63%	-1.33%	-0.57%	-0.65%
	[-3.11]	[-6.77]	[-3.59]	[-4.23]	[-3.71]	[-2.46]

breakpoints, the t-statistic of our long/short portfolio is -1.83 compared to -2.12 when decile portfolios are used. While the statistical significance may not seem drastically altered, the economic magnitude is. The value-weighted zero-cost portfolio sorted by TVOL yields an average monthly return of -1.24% due to abysmally low returns of the highest TVOL decile of -0.48% (see Panel A, Table 9). For comparison, the value of the average returns in the quintile specification is -0.61% (see Panel A, Table 3).

In the same vain, the use of decile breakpoints does not materially impact the equally-weighted portfolios' returns in terms of significance levels but has an effect on the magnitude. The average returns of long/short portfolios sorted on IVOL decrease from -0.55% to -0.65%; when sorted on TVOL from -0.54% to -0.66%; and when sorted on MAX from -0.40% to -0.45%. Furthermore, if an alternative 12/1/12 specification is employed, the statistical significance of raw returns for value-weighted portfolios does not reach the 10%

threshold. That said, the FF3 alphas stay significant under all specifications and variables of interest, therefore confirming the persistence of the anomalies despite changes in methodology.

4.2.2 Firm-specific characteristics

Ang et al. (2006) use a battery of robustness checks to rule out that the difference of returns of high and low volatility portfolios is driven by other variables that correlate with volatility. We follow Ang et al. (2006) and perform robustness checks to control for the effect of size and momentum factors in our 1/0/1 strategy.

We employ a three-stage double portfolio sorting methodology. In the first stage, all stocks are sorted into five portfolios based on the firm-specific characteristic we want to control for (i.e., size or momentum). In the second stage, each of the five portfolios is further divided into quintiles sorted by the variable of interest (i.e. IVOL, TVOL or MAX). Hence, we obtain 25 portfolios. In a final step, we then take the average across the quintiles sorted by firm-specific characteristic. As a result, each of the resulting five portfolios should have a similar average value of size or momentum but varying levels of IVOL, TVOL and MAX. The objective of this methodology is to separate the effect of the control variable on the returns from the effect of the variable of interest. In constructing the momentum measure we follow Jegadeesh and Titman (1993). In each month we measure the stock's return over the 12 months from month from $t - 13$ to $t - 1$ to establish our momentum measure[23]. Each month, we use it to sort all stocks in our sample.

Results depicted in Table 10 show that Newey-West t-statistics of the raw returns become smaller when the controls are applied. Nevertheless, the impact of controls on FF3 alphas remains limited. The FF3 alphas stay significantly negative suggesting that even after controlling for size and momentum, the long/short strategies based on IVOL, TVOL, and MAX yield significant excess returns not captured by traditional risk factors.

It is important to note that for equally-weighted portfolios, controlling for momentum reduces the absolute value of nominal returns more than when controlling for size. When

[23]We exclude the last month before the sorting as it includes the reversal to the mean effect (Jegadeesh and Titman, 1993).

Table 10: IVOL and MAX anomalies with Size and Momentum controls

To verify that the long/short strategies' negative alphas and raw returns are not driven by other factors that correlate with TVOL, IVOL, and MAX, we perform double-sorts. At the beginning of each month t, we form quintile portfolios sorted by the control variable (i.e. Size or Momentum). Within each quintile, we repeat the quintile sort, this time sorted by the variable of interest (i.e. IVOL, TVOL or MAX), resulting in 25 portfolios. For each of the quintiles sorted by the variable of interest, we then average across the corresponding five control quintiles. This allows us to obtain five portfolios with similar exposure to Size and Momentum factors but different average values of TVOL, IVOL, and MAX. "5-1" describes the zero-cost strategy. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Anomaly	First	Second	Third	Fourth	Fifth	5-1	FF3 alpha
			Panel A: Portfolios first sorted by Size				
IVOL EW	0.88	0.97	0.94	0.76	0.32	-0.56	-0.91
						[-1.89]	[-4.73]
IVOL VW	0.83	0.68	0.73	0.74	0.46	-0.37	-0.77
						[-1.24]	[-3.83]
TVOL EW	0.89	0.97	0.94	0.74	0.43	-0.46	-0.83
						[-1.53]	[-4.20]
TVOL VW	0.79	0.77	0.76	0.67	0.49	-0.30	-0.81
						[-0.84]	[-3.40]
MAX EW	0.84	1.02	0.90	0.78	0.51	-0.33	-0.69
						[-1.24]	[-3.70]
MAX VW	0.85	0.74	0.73	0.66	0.51	-0.34	-0.79
						[-1.07]	[-3.83]
			Panel B: Portfolios first sorted by Momentum				
IVOL EW	0.82	0.91	0.93	0.75	0.68	-0.14	-0.41
						[-0.63]	[-2.47]
IVOL VW	0.80	0.69	0.70	0.59	0.37	-0.42	-0.79
						[-1.74]	[-3.96]
TVOL EW	0.82	0.92	0.86	0.80	0.79	-0.04	-0.32
						[-0.17]	[-1.89]
TVOL VW	0.73	0.79	0.67	0.66	0.45	-0.28	-0.72
						[-0.94]	[-3.10]
MAX EW	0.92	0.94	0.86	0.80	0.75	-0.17	-0.46
						[-0.85]	[-2.98]
MAX VW	0.88	0.78	0.64	0.58	0.59	-0.29	-0.67
						[-1.15]	[-3.47]

portfolios are controlled for momentum, the equally-weighted zero-cost strategy sorted on IVOL yields a negative return of only -0.14% on average, and the zero-cost strategy sorted on TVOL only yields -0.04%.

Finally, it should be noted that the double-sorting methodology may be imperfect for variables with a high degree of correlation. When stocks are double-sorted with a control for size, the smallest stocks in each of the five portfolios often also fall into the highest volatility quintile during the second sorting. Therefore, we do not manage to obtain five portfolios with the same average size of stocks. For example, after double sorting on size and IVOL we achieve that the lowest volatility portfolio represents 31.4% of market capitalisation, while the highest volatility portfolio represents only 10.3%. The corresponding figures for size and MAX double sorts are 23.9% and 13.5%, respectively. Nevertheless, these market share figures are still more evenly distributed than in our original results without controls (see Table 3).

4.2.3 Exclusion of microcaps

Ang et al. (2009) use European data to confirm international evidence for the volatility pricing anomaly. The authors have been subject to criticism that the smallest stocks drive the low returns of the high volatility portfolio. Thus, the smallest 5% of stocks by market capitalisation are excluded. We follow this approach and conduct a robustness test to check if we get similar results when small stocks are excluded.

After excluding the 5% smallest stocks in each month as well as stocks for which the number of shares outstanding was not available, we get a t-statistic of -2.27 for the IVOL equally weighted long/short portfolio but only -1.60 for the value-weighted portfolio. Portfolios sorted by TVOL and MAX follow a similar pattern. Long/short returns are lower than 0 at the 5% significance level for equally-weighted portfolios, however value-weighted portfolios do not pass this threshold. Nevertheless, FF3 alphas are significantly negative for all six portfolios. Overall, when microcaps are excluded, the raw returns of equally-weighted portfolios show stronger evidence for the existence of volatility and MAX anomalies in Europe. That said, the results do not change using value-weighted portfolios.

4.2.4 Subsample analysis

Ang et al. (2006) argue that negative returns of volatile stocks may not be symmetrical and may be concentrated in bear markets. They test their hypothesis by constructing different time subsamples as well as distinguishing between recession and expansion periods, and find that the results remain robust when the data set is divided into such time periods.

With our more recent European data we obtain different results, as depicted in Table 11. The only time period where FF3 alphas pass the 10% significance level is 2013-23 when sorted on IVOL and MAX. More surprisingly, our analysis yields average positive

Table 11: Subsample analysis

We check the robustness of our results using various time subsamples. We divide the data into three ten-year subsamples as well as by economic cycles. Recession and expansion periods correspond to the NBER definitions. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

Specification	First	Second	Third	Fourth	Fifth	5-1	FF3 alpha
			Panel A: IVOL subsamples				
Jan 1993 - Dec 2002	0.68	0.50	0.39	0.24	-0.32	-1.00	-0.49
						[-1.10]	[-0.81]
Jan 2003 - Dec 2012	1.00	1.03	1.15	0.98	1.04	0.04	-0.77
						[0.06]	[-1.71]
Jan 2013 - Dec 2022	0.66	0.60	0.57	0.53	-0.51	-1.17	-1.43
						[-2.35]	[-3.32]
NBER recessions	-2.82	-2.88	-3.38	-3.74	-3.87	-1.06	1.69
						[-0.50]	[1.07]
NBER expansions	1.12	1.05	1.09	0.98	0.40	-0.72	-1.38
						[-1.93]	[-4.52]
			Panel B: MAX subsamples				
Jan 1993 - Dec 2002	0.67	0.65	0.39	0.11	-0.01	-0.68	-0.12
						[-0.76]	[-0.21]
Jan 2003 - Dec 2012	1.07	0.92	1.00	1.15	1.57	0.50	-0.28
						[0.80]	[-0.67]
Jan 2013 - Dec 2022	0.69	0.68	0.61	0.40	-0.06	-0.75	-1.03
						[-2.14]	[-3.72]
NBER recessions	-2.60	-2.95	-3.06	-3.92	-3.41	-0.81	2.08
						[-0.30]	[0.94]
NBER expansions	1.13	1.09	1.02	0.98	0.85	-0.28	-0.91
						[-0.81]	[-3.58]

raw monthly returns of the long/short strategy in the years between 2003 and 2013 for both IVOL and MAX, albeit at insignificant levels. Moreover, we do not obtain any significant relationship in the recession years and significant and negative relationship between the returns and IVOL/MAX in expansionary times. Note that for our period of analysis there are more months of expansion than recession.[24]

4.2.5 Alternative MAX specifications

Bali et al. (2011) use different MAX specifications to argue that agents have lottery-like preferences. In addition to the original specification, where MAX is defined as the one day maximum return throughout the estimation period, they also use alternative definitions - where MAX is defined as the mean value of the the highest three or highest five daily returns over the estimation period.

In this paper, we also implement this robustness check. We want to check if an alternative specification affects the significance of the FF3 alphas. We implement this robustness check on both equally and value weighted portfolios. Results depicted in Table 12 show that the FF3 alphas are robust to the choice of MAX specification as the t-statistics change only slightly across different specifications.

4.3 Volatility and MAX anomaly comparison

Bali et al. (2011) argue that the MAX effect can explain the IVOL puzzle despite the fact that the two variables are highly correlated. However, according to Hou and Loh (2016), MAX explains the whole idiosyncratic volatility puzzle purely because of its nearly perfect collinearity with volatility measures by construction. Indeed, we would expect that companies with high extreme returns have a high variance as it is defined as the average of squared deviations from the mean. Hence, large extreme returns lead to higher volatility measures by definition. Such correlation is expected to be larger for shorter measurement

[24]We use National Bureau of Economic Research (NBER) (2023) definitions to determine what months correspond to recessions (expansions). Recession periods correspond to: March 2001 to November 2001; December 2007 to June 2009; and February 2020 to April 2020. The remaining months in our data set correspond to expansionary periods.

Table 12: Alternative MAX specifications

We check if alternative specifications for the MAX strategy yield similar results to the original specification. MAX1 stands for strategies where stocks are ranked based on the one day maximum return. MAX3 indicates that stocks are ranked based on the average value of the 3 largest daily returns. MAX5 indicates that stocks are ranked based on average value of the 5 highest daily returns over the past month. All values are stated in percentage terms. Robust Newey-West t-statistics are reported in square brackets.

Specification	First	Second	Third	Fourth	Fifth	5-1	FF3 alpha
MAX1 EW	0.83	0.94	0.89	0.71	0.43	-0.40	-0.73
						[-1.24]	[-3.25]
MAX1 VW	0.82	0.77	0.69	0.59	0.50	-0.32	-0.77
						[-0.84]	[-2.94]
MAX3 EW	0.83	0.96	0.86	0.76	0.38	-0.45	-0.79
						[-1.37]	[-3.41]
MAX3 VW	0.86	0.76	0.66	0.63	0.39	-0.48	-0.97
						[-1.19]	[-3.50]
MAX5 EW	0.84	0.96	0.87	0.73	0.40	-0.44	-0.78
						[-1.36]	[-3.33]
MAX5 VW	0.83	0.78	0.69	0.62	0.41	-0.42	-0.94
						[-1.03]	[-3.13]

periods as longer measurement periods (e.g. 12 months) give a smaller weight to individual extreme values in the total variance calculation. Hence, studying the relation between these two anomalies can provide valuable insights.

Table 13 shows the correlation between various long/short portfolio returns under the 1/0/1 trading strategy. The correlation among equally-weighted portfolios is always at least 97% and correlation among value-weighted portfolios is at least 84%. The analysis of the correlation table suggests that the two anomalies are very closely related.

Bali et al. (2011) find that when controlling for the MAX effect, the high IVOL quintile yields higher returns than the low IVOL quintile. Moreover, they find that when controlling for IVOL, the long/short strategy of high MAX/low MAX still yields a negative return. This result is counter-intuitive, as the two highly correlated variables do not explain each other. We replicate the double-sorts using the IVOL and MAX variables to examine the puzzle's persistence in European equity markets. Table 14 shows the results of portfolio sorts where all stocks are first sorted by MAX and then each MAX quintile is sorted into quintiles by IVOL and vice versa. The resulting 25 portfolios are then averaged

Table 13: Correlation between IVOL and MAX anomaly

We show the correlation measures between different strategies. "VW" denominates value-weighted portfolios, "EW" denominates equally-weighted portfolios. Correlation across equally-weighted portfolios is at least 97%, while value-weighted portfolios correlate to at least 84%.

	IVOL		TVOL		MAX	
	EW	VW	EW	VW	EW	VW
IVOL EW	1.00					
IVOL VW	0.74	1.00				
TVOL EW	0.99	0.75	1.00			
TVOL VW	0.74	0.88	0.79	1.00		
MAX EW	0.97	0.72	0.98	0.75	1.00	
MAX VW	0.75	0.84	0.78	0.92	0.78	1.00

across the control quintiles[25]. As a result, we obtain five portfolios with different levels of the variable of interest but similar levels of the control variable.

In contrast to Bali et al. (2011) we do not find that the relationship between IVOL and returns becomes positive when first controlling for MAX. Moreover, when controlled for IVOL, the MAX effect becomes insignificant in both statistical and economic sense (both

Table 14: IVOL and MAX double-sorts for 1/0/1

We conduct double-sorts of MAX and IVOL measures following the methodology of Bali et al. (2011), but with quintile portfolios. "MAX and IVOL" refers to portfolios that are first sorted by MAX and then by IVOL, whereas "IVOL and MAX" stands for portfolios that are first sorted by IVOL and then by MAX. "VW" denominates value-weighted portfolios, "EW" denominates equally-weighted portfolios. When measured in VW terms, the long/short strategy does not yield statistically significant returns for either of the sorting strategies. In contrast, when we sort by IVOL controlling for MAX we obtain negative average returns.

	MAX and IVOL		IVOL and MAX	
	EW	VW	EW	VW
1	0.92%	0.72%	0.69%	0.70%
5	0.52%	0.46%	0.78%	0.61%
5-1	-0.39%	-0.26%	0.09%	-0.09%
	[-2.12]	[-1.57]	[0.92]	[-0.72]
FF3 alpha	-0.68%	-0.57%	-0.14%	-0.37%
	[-5.22]	[-3.72]	[-1.64]	[-3.20]

[25] Bali et al. (2011) perform double-sorts on decile portfolios, resulting in 100 intermediary portfolios which the authors then average across, in order to obtain 10 portfolios again.

VW and EW zero-cost portfolios have a lower than 0.1% return in absolute value). Finally, when controlling for MAX, we still find that IVOL EW has a statistically significant negative relation with returns. This suggests that, at least in the 1/0/1 strategy, the explanatory power of MAX is not strong enough to explain the IVOL anomaly.

4.4 Country-level analysis

Previous literature has mainly focused on discussing volatility pricing puzzles using U.S. data. However, evidence from smaller markets has been more limited[26]. Therefore, we also perform individual European country-level analyses. This exercise is valuable as a more unified European market for financial securities has evolved gradually over the past decades, yet some investors from individual European countries may exhibit a national market linked home-bias. Therefore, it is interesting to see if the extent of the volatility and MAX anomaly is stronger on a country or European level.

Table 15 depicts the country level results. In general, the statistical significance of both raw returns and FF3 alphas tends to be lower on country-level compared to European-level. Nevertheless, the FF3 alphas have significantly negative values in all markets except for the Netherlands and Portugal. The lower significance levels on the country level as well as a noticeably smaller t-statistics in smaller equity markets are at least to some extent due to smaller sample sizes. Specifically, there are certain countries that have a small number of companies during the early years of our analysis, and therefore, the sample period for those markets has been reduced. It is worth noting that in the Nordic markets, the volatility and MAX anomalies seem to be most pronounced. In these markets, both the FF3 alphas and the raw returns on the long/short strategy are significantly negative throughout the majority of our sample period.

Overall, despite the weaker statistical explanatory power in some countries, the direction of all three anomalies has been confirmed across markets. Of the three biggest domestic stock markets, raw returns are only statistically significant in Germany, while in the UK and France only FF3 alphas pass the 5% significance threshold.

[26]See Aboulamer and Kryzanowski (2016); Drew et al. (2006); Nartea et al. (2010).

4.5 Research limitations

4.5.1 Country-specific factor data

For their research on international evidence, Ang et al. (2009) construct three different Fama-French models to estimate IVOL on different levels. In the local model, this involves estimating the factors MKT_j, SMB_j, and HML_j for each country j. Analogously, the authors estimate a regional, and a world-Fama-French model. That said, Brooks and Del Negro (2005) show that country-specific factors of countries within one region can mainly be explained by regional factors. Therefore, we opt to use the European Fama-French factors from Kenneth R. French's website, as the countries in our sample correspond to the countries included in French's factor data. Nonetheless, we acknowledge this estimation approach as a limitation to our research since country-specific factor data could have yielded different results.

4.5.2 Estimating idiosyncratic volatility

As we attempt to follow the methodology of Ang et al. (2006) as closely as possible, we see our estimation methodology for IVOL as a limitation to our research. As laid out in Section 2, the best way to estimate idiosyncratic volatility has been extensively discussed in academic literature. While authors like Fu (2009) employ EGARCH models, other authors (e.g., Fink et al. (2012); Guo et al. (2014)) have criticised the look-ahead bias of EGARCH models. For the purpose of comparability of our results to Ang et al. (2006, 2009), we choose to estimate IVOL as the lagged realised value over preceding months.

4.5.3 Additional control variables

Ang et al. (2006, 2009) use a battery of control variables, namely leverage, liquidity risk, dollar volume, bid-ask spreads, and dispersion in analysts' forecasts. As we focus our research more on country-specific results and the interaction between IVOL and MAX, the additional controls above have not been considered. However, given the findings in Ang et al. (2006), it is unlikely that our results would have been materially impacted.

5 Conclusion

In contrast to traditional financial theory, recent literature attributes importance to a security's idiosyncratic volatility in asset pricing models. Several studies find that traditional factor models, such as the CAPM and the FF3 model, are unable to price firm-specific risk in the cross-section. That said, the effect's direction of a stock's idiosyncratic volatility on future returns is contested. Throughout recent decades, three major camps have evolved, which are either ascribing a positive, negative, or no relationship at all.

The purpose of this study has been to provide more country-level evidence to the discussion on the IVOL puzzle and the MAX anomaly, with a focus on western European countries. We follow the methodology of Ang et al. (2006, 2009), and partially extend it to complement our research with the findings of Bali et al. (2011) on the MAX effect. In a second step, we examine the relationship between IVOL and MAX in more detail.

Our results contribute to the existing literature of asset pricing anomalies in that they (1) challenge traditional financial theory (e.g. Merton (1973, 1987); Levy (1978)), (2) confirm previous findings on the IVOL puzzle and MAX effect on more granular level for western European countries (e.g. Ang et al. (2006, 2009)), and (3) delve more deeply into the relationship between IVOL and MAX (e.g. Bali et al. (2011)). We find that TVOL, IVOL, and MAX are all negatively correlated with expected returns. For portfolios based on 3, 6, and 12 month estimation windows, only value-weighted portfolios show significantly negative raw returns. Further, employing decile instead of quintile breakpoints does not materially alter our results. Controlling for Size and Momentum both reduces the significance of the zero cost strategies, both for equally-weighted and value-weighted portfolios. That said, the FF3 alphas remain negative and significant. We also find that for the MAX effect, using an average of the three or five highest daily returns over the estimation month leads to a slight increase in the significance of our results for equally-weighted portfolios, but does not markedly change the outcomes of value-weighted portfolios. Finally, we find contradicting evidence to some extent for double-sorts on IVOL and MAX, following Bali et al. (2011). In contrast to the authors, we do not see a reversal in the relationship of IVOL and expected returns when initially controlling for MAX. We conclude that the IVOL and MAX anomalies persist across the European equity markets, albeit at varying degrees of significance.

Overall, our findings question the efficiency of European equity markets. Across sorting methodologies, the zero cost strategies yield negative returns relative to traditional asset pricing models. Conversely, going short in high IVOL stocks and long in low IVOL stocks outperforms portfolios priced with factor models and yields positive alphas.

Given the detailed country-level results of this paper, further research could look into behavioural phenomena such as the home-bias of investors, and try to link it to asset pricing anomalies. Empirical approaches are needed for potential explanations for the difference in country-level anomalies in the context of a supposed integrated European equity market. Some possible avenues could include investigating the extent to which cultural and institutional differences continue to affect investor behaviour and investment decisions in different countries, even in the presence of common market structures and regulations. Moreover, the role of information asymmetry and market inefficiencies in perpetuating country-level anomalies could be explored. Ultimately, a deeper understanding of the drivers of asset pricing anomalies in the context of a regional equity market could have important implications for investors, policy-makers, and the broader economy.

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Appendix

A. Detailed country-level results for quintile portfolio sorts

Table 15: Country-level results

This table shows the results of our 1/0/1 trading strategy regarding the three market anomalies in different European countries. National stocks are filtered by location and currency criteria. The rows "5-1" represent average raw returns of the long/short strategy and the rows "FF3 alpha" depict the value of the constant relative to FF3 regressions. All values are stated in percentage terms. Robust Newey-West (1987) t-statistics are reported in square brackets.

	IVOL		TVOL		MAX	
	EW	VW	EW	VW	EW	VW
Switzerland						
5-1	-0.69	-0.30	-0.56	-0.10	-0.61	-0.17
	[-1.31]	[-0.55]	[-1.03]	[-0.16]	[-1.27]	[-0.36]
FF3 alpha	-1.08	-0.72	-0.99	-0.60	-0.95	-0.60
	[-2.76]	[-1.84]	[-2.47]	[-1.32]	[-2.50]	[-1.54]
Denmark						
5-1	-0.72	-0.76	-0.95	-0.45	-0.36	0.05
	[-1.86]	[-1.57]	[-2.34]	[-0.91]	[-0.91]	[0.13]
FF3 alpha	-1.01	-1.12	-1.28	-0.88	-0.60	-0.24
	[-3.05]	[-2.51]	[-3.68]	[-1.94]	[-1.76]	[-0.62]
France						
5-1	-0.45	-0.55	-0.48	-0.41	-0.55	-0.36
	[-1.16]	[-1.07]	[-1.22]	[-0.80]	[-1.51]	[-0.82]
FF3 alpha	-0.76	-0.93	-0.82	-0.96	-0.84	-0.76
	[-2.48]	[-2.18]	[-2.73]	[-2.23]	[-2.91]	[-1.98]
Belgium						
5-1	-0.56	-0.28	-0.44	-0.12	-0.35	-0.14
	[-1.51]	[-0.51]	[-1.23]	[-0.22]	[-1.14]	[-0.33]
FF3 alpha	-1.03	-0.80	-0.94	-0.78	-0.80	-0.68
	[-4.23]	[-1.91]	[-3.90]	[-1.96]	[-3.58]	[-1.96]
Spain						
5-1	-0.51	-1.15	-0.45	-1.24	-0.32	-1.10
	[-1.43]	[-2.69]	[-1.33]	[-2.77]	[-1.14]	[-2.92]
FF3 alpha	-0.90	-1.49	-0.92	-1.67	-0.74	-1.46
	[-2.91]	[-3.56]	[-3.05]	[-3.93]	[-2.88]	[-4.21]

Table 15 (continued)

	IVOL		TVOL		MAX	
	EW	VW	EW	VW	EW	VW
Italy						
5-1	-0.70	-0.64	-0.68	-0.55	-0.67	-0.34
	[-2.75]	[-1.50]	[-2.57]	[-1.21]	[-2.86]	[-0.86]
FF3 alpha	-1.05	-1.05	-1.08	-1.09	-1.02	-0.75
	[-4.76]	[-2.76]	[-4.72]	[-2.82]	[-5.14]	[-2.06]
Germany						
5-1	-1.21	-1.26	-1.21	-1.04	-0.96	-0.79
	[-2.51]	[-2.78]	[-2.46]	[-1.92]	[-2.04]	[-1.54]
FF3 alpha	-1.48	-1.39	-1.51	-1.31	-1.24	-1.10
	[-3.94]	[-3.35]	[-3.92]	[-2.91]	[-3.49]	[-2.79]
Finland						
5-1	-1.14	-1.22	-1.21	-1.18	-0.73	-0.67
	[-2.94]	[-2.28]	[-2.94]	[-2.37]	[-2.00]	[-1.43]
FF3 alpha	-1.35	-1.52	-1.47	-1.49	-0.94	-0.88
	[-4.08]	[-3.41]	[-4.08]	[-3.54]	[-3.00]	[-2.26]
Netherlands						
5-1	-0.21	0.81	-0.09	0.33	-0.28	0.28
	[-0.42]	[1.50]	[-0.19]	[0.61]	[-0.78]	[0.62]
FF3 alpha	-0.52	0.49	-0.43	-0.12	-0.58	-0.13
	[-1.34]	[1.02]	[-1.11]	[-0.26]	[-1.91]	[-0.31]
Norway						
5-1	-0.99	-0.79	-1.04	-0.76	-0.64	-0.61
	[-2.04]	[-1.47]	[-2.12]	[-1.31]	[-1.58]	[-1.22]
FF3 alpha	-1.30	-1.07	-1.37	-1.09	-0.88	-0.89
	[-3.27]	[-2.18]	[-3.41]	[-2.07]	[-2.59]	[-2.09]

Table 15 (continued)

	IVOL		TVOL		MAX	
	EW	VW	EW	VW	EW	VW
Sweden						
5-1	-1.18	-0.90	-1.16	-0.88	-1.04	-0.65
	[-2.64]	[-1.85]	[-2.50]	[-1.85]	[-2.57]	[-1.59]
FF3 alpha	-1.34	-1.13	-1.33	-1.19	-1.24	-0.95
	[-3.70]	[-2.55]	[-3.74]	[-2.83]	[-3.82]	[-2.74]
UK						
5-1	-0.35	-0.37	-0.38	-0.55	-0.20	-0.25
	[-0.90]	[-0.83]	[-0.96]	[-1.15]	[-0.57]	[-0.61]
FF3 alpha	-0.71	-0.85	-0.75	-1.08	-0.51	-0.66
	[-2.27]	[-2.70]	[-2.39]	[-3.19]	[-1.80]	[-2.15]
Portugal						
5-1	-0.03	-0.90	0.18	-0.29	-0.14	-0.57
	[-0.06]	[-1.81]	[0.44]	[-0.54]	[-0.39]	[-1.28]
FF3 alpha	-0.18	-1.26	0.02	-0.62	-0.32	-0.88
	[-0.47]	[-2.55]	[0.05]	[-1.13]	[-0.91]	[-1.97]