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Are extreme returns priced in the stock market? European evidence

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ABSTRACT

This paper revisits some recently found evidence in the literature on the cross-section of stock returns for a carefully constructed dataset of euro area stocks. First, we confirm recent results for US data and find evidence of a negative cross-sectional relation between extreme positive returns and average returns after controlling for characteristics such as momentum, book-to-market, size, liquidity and short term return reversal. We argue that this is the case because these stocks have lottery-like characteristics, which is attractive to certain investors. Also, these stocks tend to be very volatile so that arbitrageurs are discouraged from correcting potential mispricing. As a consequence, these stocks are often overpriced and hence face lower expected returns. Second, when we control for extreme returns, the recently found negative relationship between idiosyncratic risk and future returns is less robust. In our models, after adding maximum returns, the relationship is insignificant and sometimes even positive. We also find that idiosyncratic skewness and coskewness play an important role for asset pricing, as predicted by several theoretical models.

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1. Introduction

Despite decades of research, it is still not completely clear what determines cross-sectional variation in expected stock returns. It is well accepted that the four factor model of Fama and French (1993) and Carhart (1997) goes a long way in capturing this return variation. Nevertheless, empirical studies continue to document other characteristics that are related to average stock returns (see Fama and French (2008) for a recent overview). As most of these characteristics do not follow directly from theory, they are subject to the data-mining critique implying the patterns are mere statistical flukes (Lo and MacKinlay, 1990). In any dataset, some results are bound to be statistically significant just by chance. One way to address this critique is to look for corroborating evidence on other markets or from other periods.

In this paper, we verify the US results of Bali et al. (2011) on a carefully constructed euro area stock market database covering more than 30 years. More specifically, Bali et al. (2011) find a statistically and economically significantly negative relation between the maximum daily return over the past 1 month and expected stock returns. They argue that this captures individual investors' preference for lottery-like stocks, i.e. stocks that have a low probability of a huge profit and a large probability of a small loss as shown by Kumar (2009). Although this is an idiosyncratic characteristic, demand by individual investors may lead to higher prices (and lower expected returns) for these stocks, given that these investors typically hold underdiversified portfolios, see e.g. Odean (1999) and Goetzmann and Kumar (2008). We show that this effect also exists in the euro area. Moreover, it is unlikely to be arbitraged away by large investors as the typical stock with extreme positive returns is relatively small, illiquid and has relatively high idiosyncratic volatility. Even if short selling these stocks were possible, it would expose arbitrageurs to considerable risk. Hence, it is plausible that individual investors drive the pricing of such stocks.

We also look at idiosyncratic skewness and coskewness and find that the maximum return effect is robust to including total skewness, idiosyncratic skewness or coskewness. Moreover, we find that both idiosyncratic skewness and coskewness are significantly negatively related to expected returns. Lastly, the comovement between maximum returns and idiosyncratic volatility is investigated. Taken on its own, idiosyncratic volatility is negatively related to expected returns. The relation is statistically significant and goes in the direction of the puzzling results of Ang et al. (2006) for the US and Ang et al. (2009) for an international sample of stocks. However, when we control for extreme positive returns,

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the relation between idiosyncratic risk and expected returns becomes less robust. This may also be due to multicollinearity as discussed by Ahn et al. (2013). Nevertheless, correcting for multicollinearity does not change the conclusion that extreme positive returns are negatively priced.

The remainder of the paper is structured as follows. In Section 2, we discuss sample selection, construction of variables and filters. Next, we discuss the main results in Section 3. Section 4 provides the results of a battery of robustness checks and finally, we conclude.

2. Data

2.1. Sample selection

Our sample comprises thirteen European countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, the Netherlands, Portugal, Slovakia and Spain. Following Schmidt et al. (2011) we exclude the other four countries of the euro area (Malta, Estonia, Cyprus and Slovenia) as their financial impact on the euro area is negligible. In 2009, they contributed only 0.80% of the euro area GDP. We are therefore convinced that the current sample is representative for the entire euro area. All data come from Thomson DataStream (TDS) as in Ang et al. (2009). We include both active shares and delisted shares[3] thereby minimizing survival bias in our sample. The resulting dataset is then subjected to extensive filtering as described in Appendix A in order to select only common stock issues. This results in a sample of 7861 European companies. For these companies, we download the end-of-month return index (including dividends), unadjusted stock price, market capitalization (*MC*) and book-to-market ratio (*B*/*M*), from 31 December 1979 to 30 June 2011. Additionally, we download the daily total return index and *MC* over the same period. TDS automatically calculates *B*/*M* by dividing the book value per share by market value per share at time *t*, where book value per share is from the company's last fiscal year (Worldscope item 05476). For the pre-1999 period all data are converted by TDS into synthetic euro. As the risk-free rate, R_f, the monthly money market rate as reported by Frankfurt banks is used.[4]

2.2. Construction of variables

All returns are calculated using the TDS total return indices. Two procedures, inspired by Ince and Porter (2006) and Schmidt et al. (2011), are used to correct errors that occasionally occur in the TDS database. First, we need to tackle decimal errors. Suppose the return index is 101.52 on a particular day and does not change the next day. When TDS correctly stores 101.52 the first day, but erroneously stores it as 1015.20 the second day, using a computed return of 900% instead of the true zero return would obviously distort results. We call this a right-decimal error, because the decimal moved erroneously to the right. Alternatively, a left-decimal error occurs when TDS erroneously stores the return index on the second day as 10.152, which would result in a −90% return. These examples all show nonzero returns while the true return is zero. Additionally, we could have decimal errors when the true return is nonzero. For example, when the return index decreases from 101.52 to 96.44 (−5% true return) but is stored as 964.40, this results in a computed return of 849.96%. This example shows that there is a need to account for decimal errors in both directions, whether the true return is zero or nonzero. We therefore omit any returns that are above 400% (a −50% true return accompanied by right-decimal error) or below −85% (a 50% true return accompanied by a left-decimal error). A second correction is to set both R_t and R_{t-1} to missing if R_t or R_{t-1} is greater than 300% and $(1 + R_{t-1})(1 + R_t) - 1$ is less than 50% (indicating extreme reversal), both for monthly and daily returns. Excess returns are calculated using the risk-free rate. *MC* and *B*/*M* are not corrected as no obvious errors are detected. In the analyses that follow, we use twelve lags for *B*/*M* to ensure that accounting data is always available to investors at the time.[5] Since Jegadeesh and Titman (1993) the momentum effect is widely recognized and accepted in the literature on cross-sectional return predictability. Therefore, we also include it in our regressions and sorting algorithms. As in Fama and French (2008), momentum (*Mom*) in month *t* equals the buy-and-hold return of a particular stock over the period from month $t-12$ to month $t-2$. We use the return of month $t-1$ (*LagRet*) separately to control for the short-term reversal effect documented by Jegadeesh (1990). We compute a very simple measure of expected illiquidity (*Illiq*) inspired by Bekaert et al. (2007). *Illiq* in month *t* is the proportion of zero returns observed over the last 260 trading days prior to month *t*. We did not use the Amihud (2002) measure as it would result in a major loss of observations: for the 2,971,458 firm-months, only 649,433 observations (or 22%) on volume are available. Lastly, we use the skewness coefficient (*Skew*) of the last 260 daily returns prior to month *t* as a proxy for expected skewness. If not all 260 daily returns are available, we ignore the missing values, but a minimum of 65 daily observations is required. If not, *Skew* is set to missing. We also calculate the four factors (market, *SMB*, *HML* and *WML*) advanced by Fama and French (1993) and Carhart (1997) to calculate portfolio alphas. The calculation of the factors is based on our own dataset. A detailed description is available in Appendix B.

As admitted by Bali et al. (2011), who estimate beta over a month using daily data, this estimate is subject to a significant amount of measurement error. We therefore decide to follow another, more robust approach. Market beta, *SMB* beta and *HML* beta in month *t* are calculated using a minimum of 24 and a maximum of 60 monthly excess stock returns from months prior to month *t*. If less than 24 returns are available, market beta is set to missing. The following time-series regression model is estimated[6]:

$$R_{i,t} - R_{f,t} = \alpha_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \quad (1)$$

If the beta estimate is smaller than −1 or larger than 5, we set it to missing. These boundaries are quite arbitrary. However, the estimated betas are actually proxies of expected future beta and it would be hard to argue that any investor would expect more extreme betas. Not using these boundaries would result in betas as high as 50. We also need a proxy for expected idiosyncratic volatility (*IVol*) in month *t*. To account for the time-varying volatility of

[3] The lists used are: WSCOPEOE, ALLAS, DEADOE (Austria); WSCOPEBG, FBDO, DEADBG (Belgium); WSCOPEFN, FFIN, DEADFN (Finland); WSCOPEFR, FFRA, ALLFF, DEADFR (France); WSCOPEBD, FGER1, FGER2, DEADBD1, DEADBD2 (Germany); WSCOPEIR, FIRL, DEADIR (Ireland); WSCOPEIT, FITA, DEADIT (Italy); WSCOPENL, FHOL, ALLFL, DEADNL (The Netherlands); WSCOPEPT, FPOM, FPOR, FPSM, DEADPT (Portugal); WSCOPEES, FSPN, DEADES (Spain); WSCOPELX, FLUX, DEADLX (Luxembourg); WSCOPEGR, FGREE, FGRPM, FGRMM, FNEXA, DEADGR (Greece); FSLOVAK, FSLOVALL, DEADSLO (Slovakia).

[4] This rate can be found on the website of the Deutsche Bundesbank in the time series database.

[5] Using a constant lag of 12 months does not always reflect the most recent information. We may sometimes use the book-to-market ratio of 12 months ago when in fact new accounting data had already reached the market. We argue that the book value of equity is very persistent and that short-term variation in book-to-market ratios will mainly be caused by variation in stock prices. The fact that the value effect is still very strong in our data (see later) confirms this intuition.

[6] We refrain from adding the WML factor as exposures with respect to it are much less persistent due to the relatively short-lived nature of momentum. Nevertheless, when we do use the WML exposure, differences in *b*, *s* and *h* across both factor models are minimal: correlations are respectively 0.93, 0.97 and 0.89. Moreover, the correlation between market betas from the three factor model and traditional CAPM betas is 0.88, or 0.80 when we use Dimson (1979) betas with one lag. Using these other estimators in our analysis does not impact the results in any significant way.

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