Diversification Risk Premium

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Abstract^{**}

A long criticism on the usefulness of the traditional CAPM model has been raised in the vast literature of arbitrage pricing models that proposes everal risk factors on firm fundamentals orinvestigate the stochastic properties of stock returns' distributions, (Fama and French (2004)). However, our paper provides evidence of misspecification issues in the empirical formulations of most of these multifactor models. We reveal that existing self-financing strategies on size, value, momentum, liquidity and financial distress may contain residual idiosyncratic risk because of the existence of asymmetric diversification effects. Using data from the main US exchanges, there is strong evidence of over- and under-estimation of factor risk premiarelevant to their intrinsic values. We propose an amended multifactor asset pricing model, the diversification risk premium model, to control for the intertemporal asymmetric idiosyncratic risk. Overall, our results suggest that portfolios formed on size and liquidity suffer from diversification asymmetries. Specifically, the size effect dies out when the asymmetric effect on idiosyncratic risk is accounted for. Moreover, investing on valued and financially distressed firms yields consistently positive returns associated with the systematic component of risk of the corresponding risk factors. Finally, there is evidence that the presence of risk factors is enhanced during periods of low inter-dependencies between securities' returns.

Keywords: diversification risk premium, diversification, risk premium, multifactor

JEL Classification: G11, G12, G14

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1. Introduction

In the last decades, many researchers have examined the dynamics of asset pricing models, either by addressing the theoretical underpinnings and importance of the documented stylized factors or by quantifying the time series properties of the estimated parameter set. These dynamics are typically investigated with a portfolio-based approach which aims to yield positive abnormal returns and in addition arbitrage away any opportunity that does not coincide with the principal risk-return trade-off.

While Sharpe's (1964) capital asset pricing model - CAPM - under specific, and often heroic, assumptions, lay on the security market line that comprises exclusively the beta risk with respect to the market portfolio, a hypothetical portfolio (Roll (1977)), it fails to provide consistency through time and/or across firm fundamentals. A significant contribution on the former aspect of this literature is Merton's (1973) intertemporal capital asset pricing model – ICAMP – according to which investors optimize their portfolios considering the intertemporal relationship of expected returns with future state variables. The latter inconsistency motivated many researchers, among them Fama and French (1993), to propose extensions that accountfor several stylized financial facts that associate investors' expectations with firm fundamentals. While the statistical significance of these characteristics, thatdo not, necessarily, represent state variables of concern to investors, on multifactor models, enhance the criticism against CAPM, Ang and Chen (2007) argue that they could be fully accounted for by a one-factor with time varying factor loadings, providing evidence in favor to the conditional CAPM.

The review papers by Schwert (2002) and Malkiel (2003) highlight this criticism and provide evidence that several of the stylized facts tend to be weaker after the papers which highlighted them were published, or be viewed as short-term aberrations of a long-term efficient market.

This argument could be illustrated employing annual data from Kenneth French's Data Library^{††}as shown in Figure 1 (three subfigures). The primary line in these figures represents the equally-weighted returns of self-financing strategies. They are based on some of the most commonly cited drivers of extraordinary equity returns, including capitalization (small minus

^{††}<u>http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html</u>

big: SMB), book-to-market value (high minus low: HML) andpast performance momentum (winners minus losers: WML). These factors, which are scaled on the left vertical axis, represent the annualized return of the long-short self-financing portfolio strategies of the extreme (bottom and top) 10th percentiles, for a time period spanning from 1927 to 2011. The time series subfigures reveal that these strategies seem to obtain both positive and negative excess returns on average. Notably, financial crises such as the great recession, the 1973 oil crisis, the long-term capital management (LTCM) collapse, the burst of the Dot-com bubble and the recent credit crunch have strongly impacted the estimated factors differently. The relevant ratio of the extreme portfolios' inherent risk, as approximated for by the annual realized volatility of monthly returns, is illustrated on the secondary lines of the subfigures. This graph portrays the inconsistent riskreturn factor trade-off over time, particularly during financial crises. Specifically, there are periods of time where although the SMB strategy awards investors, the small portfolio exhibits a lower risk profile than that of the corresponding big one. As regards the HML factor, there are periods of time where valued firms outperform growth firms but with a lower inherent risk. Similar conclusions could be made from the third subfigure with respect to the WML strategy. Vis-à-vis variability, the risk premium foundation of these strategies as a solid asset pricing risk factor may be questioned.

Please insert Figure 1 about here

Figure 2 presents a moredetailed depiction of the annualized SMB and HML factors using monthlyreturns for a period of 30 years (1980-2011) from the same source. During this period, the relative risk ratio of the top and bottom extreme portfolios is inconsistent with a risk-averse investor's profile. For example, as shown at the first subfigure, at the beginning of 1990's and during the recent financial crisis the SMB comprises a profitable strategy, but the inherent risk (realized portfolio risk) of big portfolios is higher than that of small portfolios (by 50% to100%). Similarly, the second subfigure shows that although the HML trading strategy awards investors consistently over time, theportfolio of valued firms, exhibits lower realized risk than that of growth firms.

Please insert Figure 2 about here

The same inferences could be reached from another point of view, by separately considering (for each component of the long-short strategy) the daily GARCH conditional volatility(Bollerslev (1986)). The first subfigure contains two figures that illustrate the conditional volatility of portfolios on capitalization (big and small firms) and the ratio of the portfolio risk of big over small firms, respectively. High capitalization firms exhibit a higher risk (up to four times with respect to low capitalization) in the extreme portfolios. The second subfigure contains two figures that illustrate the conditional volatility of portfolios on book-to-market value(valued and growth firms) and the ratio of the portfolio risk of valued over growth firms, respectively. Value firms exhibit higher risk (up to 2 times) than that of growth firms. Moreover, the overall risk of the SMB and HML trading strategies does not coincide consistently with the relative riskiness of the extreme portfolios on size and on value.

Please insert Figure 3 about here

This illustrative exposition of the ex-post inconsistently divergent extreme portfolio volatility motivates us to consider a model with an asymmetric covariance structure. To the extent that potential asymmetric diversification effects of self-financing portfolio strategies exacerbate their risk, the latter needs to be factoredout, in order to establish the net inherent risk of the regressed factors. The conventional implementation of trading strategies on stylized firm fundamentals does not account for possible asymmetric diversification of the extreme portfolios. Hence, self-financing portfolio strategies, which aim to serve as proxies for several economic effects, reward investors not only for their exposure to the systematic component of risk but also for asymmetries on the idiosyncratic component. Thus, theycan be criticized for their incompetence to capture asymmetric diversification effects, since the extreme portfolios involved in the strategy are incompatible with each other in terms of the within inherent interrelationship between securities. Such inconsistencies in the covariance matrix of the distributions of returns raise misspecification issues in multifactor asset pricing models, leading to potential questionable results in the examination of informational efficiency.

A plethora of papers addresses the asymmetric covariance matrix effects with respect to firm fundamentals, attributing them to the fact that aggregate information potentially affects firstly big and well-established firms and subsequently smaller. For example, Conrad, Gultekinand Kaul (1991) documented a distinct asymmetry in the predictability of the volatilities of big and small firms, which is indicative of a spillover effect from high capitalized firms to small ones. Specifically, they applied univariate and multivariate GARCH models and found asymmetries in the predictability of volatilities of large vs. small firms. They argue that volatility shocks of big firms affect the returns of big and small firms, while shocks to smaller firms have no impact on the behavior of either the mean or the variance of big firm returns.

Moreover, Kroner and Ng (1998) investigate several time-varying covariance models and emphasize the importance and the role that the imposed restrictions play on the effects of past shocks to the forecasted covariance matrix. The (volatility) leverage effect could also be present in the non-diagonal elements of a covariance structure, with significant implications for portfolio management of firms with high leverage. Finally, they propose a general asymmetric model, the General Dynamic Covariance (GDC) Model, to investigate the dynamic relation between big and small firm returns concluding that symmetric multivariate GARCH models are misspecified. Moreover, they find significant spillover effects from big to small firms and, most importantly, they address significant asymmetric effects on the conditional covariance matrix with respect to market capitalization. They also find asymmetric effects in the variance-covariance matrix; bad news related with big firms causing volatility in both small and big firm returns. Moreover, the leverage effect on the volatility process has a higher magnitude for big firms.Although the applied symmetric models were misspecified, the GDC model suggests that big firm returns can affect the volatility of small firms, while a causal effect in the opposite direction does not exist.

Our work is motivated by Ang and Chen (2002), who developed a correlation statistic that considers the asymmetries due to the downside and upside moves of the random variables involved in conditional factor models. They impose a conditional correlation (H statistic) in a switching-regime model which is fundamentally different from other measures of asymmetry, such as skewness and co-skewness. Using different portfolios on firm fundamentals they apply the H-statistic and find that correlation asymmetry is increased in portfolios of small (compared to big firms), value (compared to growth firms) and loser firms (compared to winner firms) according to the past twelve month performance. Greater asymmetries between portfolios formed on size, value and badpast performance imply greater potential diversification effects of the trading strategy. This is one of the most important motivation of our paper. The authors state that

"while Fama and French (1993) observe size and value premia, portfolios formed on these characteristics may be more risky by their greater correlation asymmetry than by measuring risk only by second moments". In other words, small-value firms might yield extraordinary positive returns because of the asymmetry that is documented on the long and short portfolios that comprise the strategy.

Based on the seminal work of Markowitz (1952), which suggests that the correlation structure of asset returns is the cornerstone of portfolio analysis, we introduce a multifactor asset pricing model, in which possible asymmetries in the covariance matrix related to firm fundamentalsare directly embedded in the pricing mechanism. According to Markowitz (1959), in an equally-weighted portfolio of n securities with identical individual risk (σ_i) and pairwise covariance (cov_{i,j}), the expected portfolio variance depends on the average variance and covariance:

$$\overline{\sigma}_{portfolio}^{2} = \frac{1}{n} \cdot \overline{\sigma_{i}^{2}} + \left(1 - \frac{1}{n}\right) \cdot \overline{\operatorname{cov}_{ij}} = \frac{1}{n} \cdot \overline{\sigma_{i}^{2}} + \left(1 - \frac{1}{n}\right) \cdot \overline{\sigma_{i}^{2}} \cdot \overline{\rho_{ij}}$$
(1)

where i and j stand for the indication of an individual security.

The idea behind this decomposition in idiosyncratic and systematic components is that for a specific asset class that exhibits a relatively low correlation structure $(\overline{\rho_{ij}})$, the portion of specific risk is decreased, implying higher diversification benefits. On the other hand, a selffinancing portfolio strategy reflects the excess return of a group of firms over another because of the riskiness of these portfolios. Thus, a self-financing portfolio strategy assumes no beta risk with respect to the market portfolio. Assuming a sufficiently large number of firms on each extreme portfolio, it is expected that the long-short portfolio strategy constitutes a risk factor awarding investors for the systematic component of risk they are exposed to, as expressed in the second component of equation (1). However, the ability to diversify away the idiosyncratic component of risk could vary across the extreme portfolios of the risk factors, imposing an imperfection on the formulation of portfolio strategies. This imbalance of the diversification ability would result in an asymmetry of the remaining idiosyncratic risk on the extreme portfolios. This portion of risk, which differs among the extreme portfolios and should not be priced, is nevertheless not accounted for in conventional multifactor asset pricing models. The objective of this paper is to quantify this element of inherent risk misdiversification of stylized factors related to firm fundamentals such as capitalization, book-to-market value, momentum on past performance, liquidity and financial distress. A multifactor model is proposed, in which possible asymmetries in the covariance matrix with respect to firm fundamentals are directly priced, comprising a diversification premium for each factor. Our paper contributes to the extant literature by considering the inherent risk-diversification of various well-known stylized effects, and by determining the intrinsic value of the trading strategies, along with the expected premia due to discernible patterns on the correlation structure. The importance of our findings concerns both academics and market participants, by shedding light on the informational context of multifactor models and by revealing more attractive trading strategies for both institutional and individual investors.

The rest of the paper is organized as follows. Section 2introduces the theoretical background of the asset pricing model that is proposed. Section 3 presents the literature review. Section 4 discusses the research methodology and Section 5 discusses the empirical findings. Section 6 considers several robustness checks and finally, Section 7 concludes.

2. Theoretical Background

Any extraordinary yield from a trading strategy could be attributed either to market anomalies or to risk factors, depending on the multifactor model employed. Stylized factors not captured in any set of explanatory variables could erroneously be attributed to a market anomaly. The same effects could be adequately priced in a model, comprising additional risk factors. Moreover, in an efficient market the economic significance of a risk factor diminishes whenever its risk-adjusted component remains profitable. In an efficient market, prices should obey the risk-return trade-off that rational market participants impose. Fama (1970) underlined the role of past and current information in the quantification of equilibrium expected returns.

Most of the financial stylized facts that are based on firm fundamentals such as size and value characteristics, past performance, liquidity and financial distress are typically captured by self-financing trading strategies, according to which a long position is held on underpriced assets

and a short-selling one on overpriced assets, respectively. Although this strategy would potentially render gains to investors, its statistical significance and, most importantly, its economic foundation should be revisited. The key factor in the determination of these factors is risk. Since trading strategies refer to long-short portfolios (extreme portfolios), the correlation structure of these extreme portfolios should also be considered.

Possible asymmetric diversification benefits of the extreme portfolios that form the longshort trading strategy on fundamentals are not considered in conventional asset pricing models or their extensions, such as Fama and French (1993), Carhart (1997).

In the absence of diversification benefits the expected rewards of the representative security *i* belonging to an asset class portfolio would be based on the individual representative Sharpe ratio $\overline{SR_i}$, where r_f denotes the risk free interest rate:

$$r_{CML, p, NO \text{ diversification benefits}} = r_f + \overline{SR_i} \cdot \sigma_p = r_f + \frac{E(r_i) - r_f}{\overline{\sigma_i}} \cdot \sigma_p$$
(2)

However, investors dealing with a portfolio (p^*) which consists of securities from the same asset class would enjoy a superior reward per unit of risk (SR_{p^*}) , due to potential diversification benefits. A portfolio consisting of many securities from an asset class would offer at least the same return (r_{p^*}) for a lower level of risk: $st.dev_{p^*} = \sigma_{p^*}$, and any attempt to leverage this diversified portfolio would result in a security market with greater slope:

$$r_{CML, p, diversification \ benefits}^{*} = r_f + SR_{p^*} \cdot \sigma_p = r_f + \frac{r_{p^*} - r_f}{\sigma_{p^*}} \cdot \sigma_p \tag{3}$$

A critical question arises regarding the decomposition of portfolio returns $p^*(r_{p^*})$ to an intrinsic component and another relevant to the potential diversification effects. Any direct comparison between the representative security (*i*) and the portfolio (p^*) that investors obtain is misleading, unless the necessary risk-adjustment has taken place. By leveraging the representative security (*i*) in equation (2) we could obtain the returns of a risk-equivalent portfolio (p^{**}) which has no diversification benefits:

$$r_{CML, p, NO \, diversification \, benefits \mid \sigma_{p^*}}^{**} = r_f + \overline{SR_i} \cdot \sigma_{p^*} = r_f + \frac{E(r_i) - r_f}{\overline{\sigma_i}} \cdot \sigma_{p^*}$$
(4)

Equations (3) and (4) express the risk-return trade-off of securities of a specific asset class, with and without diversification benefits, respectively, evaluated at the same level of risk(σ_{p^*}), which corresponds to the risk that investors undertake by holding a portfolio of these securities. The difference between these returns represents the diversification benefit, which is embedded in the specific asset class projected at the risk level of the portfolio consisting of many securities (r_p^*, σ_p^*):

$$DB_{p|\sigma_{p^{*}}} = r_{CML, p, diversification \ benefits} - r_{CML, p, NO \ diversification \ benefits} = r_{p^{*}|\sigma_{p^{*}}} - r_{p^{**}|\sigma_{p^{*}}} = SR_{p^{*}} \cdot \sigma_{p^{*}} - SR_{i} \cdot \sigma_{p^{*}}$$

$$DB_{p|\sigma_{p^*}} = \frac{r_{p^*} - r_f}{\sigma_{p^*}} \cdot \sigma_{p^*} - \frac{E(r_i) - r_f}{\overline{\sigma_i}} \cdot \sigma_{p^*} = \left(r_{p^*} - r_f\right) - \left(E(r_i) - r_f\right) \cdot \frac{\sigma_{p^*}}{\overline{\sigma_i}}$$
(5)

Thus, the diversification benefit, in terms of returns, which is embedded in portfolio p^* , consists of two terms, the excess return of the portfolio over the risk free interest rate (r_f) and the excess return of the representative security over the r_f multiplied with the ratio of risk of the portfolio and the representative individual security. Lower values of the ratio imply a strong persistence of idiosyncratic risk and potentially a greater weight on the negative term of the diversification benefit formulation. The lower the correlation structure within a specific asset class, the lower its portfolio variability and, consequently, the higher the diversification benefits. Clearly, the diversification benefit for a specific asset class is affected by the inherent diversification within this asset class.

Any possible difference in the correlation structure of the two portfolios that comprise the self-financing long-short trading strategy imposes an asymmetric diversification return benefit. The latter could be expressed as an expected diversification premium:

 $\pi_{asymmetric\ diversification} = DB_{returns}^{long} - DB_{returns}^{short}$

$$\pi_{asymmetric \ div.} = \left[\left(r_{p^{*}}^{long} - r_{f} \right) - \left(E\left(r_{i}^{long}\right) - r_{f} \right) \cdot \frac{\sigma_{p^{*}}^{long}}{\sigma_{i}^{long}} \right] - \left[\left(r_{p^{*}}^{short} - r_{f} \right) - \left(E\left(r_{i}^{short}\right) - r_{f} \right) \cdot \frac{\sigma_{p^{*}}^{short}}{\sigma_{i}^{short}} \right]$$

$$(6)$$

This premium (π) captures possible asymmetric effects on the diversification benefits of the extreme portfolios of long-short self-financing trading strategies. Multifactor models that do not account for possible asymmetric diversification benefits would potentially overestimate or underestimate (depending on the direction of the trading strategy)^{‡‡}the magnitude of stylized factors, causing misspecification issues and leading to mispricing of asset returns.

Assuming that investors hold an equally-weighted portfolio then the diversification risk premium could be expressed in a simpler way, since the (EW) portfolio return should be equal to that of the individual representative security:

$$\pi_{asymmetric \ div.} = \left[\left(r_{p^*}^{long} - r_f \right) - \left(r_{p^*}^{long} - r_f \right) \cdot \frac{\sigma_p^{long}}{\sigma_i^{long}} \right] - \left[\left(r_{p^*}^{short} - r_f \right) - \left(r_{p^*}^{short} - r_f \right) \cdot \frac{\sigma_p^{short}}{\sigma_i^{short}} \right] \quad \text{or}$$

$$\pi_{asymmetric \ div.} = \left(r_{p^*}^{long} - r_f \right) \cdot \left(1 - \frac{\sigma_p^{long}}{\sigma_i^{long}} \right) - \left(r_{p^*}^{short} - r_f \right) \left(1 - \frac{\sigma_p^{short}}{\sigma_i^{short}} \right) \quad \text{or}$$

$$\pi_{asymmetric \ div.} = r_{p^*}^{long^*} \cdot \left(1 - \frac{\sigma_p^{long}}{\sigma_i^{long}}\right) - r_p^{short^*} \left(1 - \cdot \frac{\sigma_p^{short}}{\sigma_i^{short}}\right)$$
(7)

Equation (7) dictates that the diversification risk premium depends on the sign of the implemented long-short strategy and on the relevant relationship of portfolio and individual risk for the two extreme portfolios. More specifically each term of the long-short portfolio strategy is adjusted according to its inherent diversification benefit, resulting to greater multipliers for extreme portfolios with lower inherent diversification. For instance, if the long position consists of shares with greater diversification ability than that of the short position, the proposed premium of equation (7) would impose heavier penalty for the short position, leading to greater

^{‡‡}If the long position is related to lower correlated securities than the short one, then the factor is overestimated, while opposite results hold when buying the portfolio with highly correlated securities.

discrepancies between the excess returns of the long and short portfolios, over and above the risk free interest rate.

3. Brief Literature Review

A paper which contributes to the debate on the usefulness of firm fundamentals on the explanation of the cross sectional of securities returns and its implications on the examination of the market efficiency, is Moskowitz's (2003).He investigates the relationship between premia associated with firm fundamentals and the covariance matrix of returns. He argues that if covariance risk is priced, then establishing such a link can aid in determining whether the premia associated with firm fundamentals are due to risk or mispricing. He also suggests that even if covariance risk is not priced, the results may still shed light on informational efficiency. Based on portfolios on size and value characteristics, he finds that out-of-sample volatilities do not exhibit a pattern across factor models as previously argued. This suggests that the magnitude of the variance terms is an important element in forming efficient portfolios which comprise a risk factor. According to his empirical findings, the SMB factor is linked to returns' second moments.

The most important factors of asset pricing models commonly used in this literature are associated with size, value and momentum effects. The size effect which was documented mostly on papers that used data during the period before 1980's, has been criticized for the lack of its economic significance, see among others, Banz (1991), Keim (1983) and Chan and Chen(1991). It is not clear whether the size effect comprises a risk factor or if it just proxies for other unknown factors which depend on firm capitalization. Although size effect does not comprise market inefficiencies, its existence implies model misspecification. Moreover, the informational content is associated with firm capitalization which potentially yields higher returns for smaller firms. Undoubtedly, illiquidity of small securities and thin trading causes a downward bias to the estimated systematic beta that consequently yields an abnormal return, the size effect. Similarly, small firms tend to be marginal firms which are exposed to production risk and they are less likely to survive adverse economic conditions especially when they are financially distressed. One of the most important contributions on the economic significance of size effect was that of Vassalou and Xing (2004) who formed portfolios on size and default risk (distance to default measure) and found that apparently, default risk, is the source that gauges the size effect.

The value effect traces back in 1960's with the seminal work of Nicholson (1960, 1968) where trading in valued securities, i.e. low price-earnings ratio, yielded on average positive abnormal risk-adjusted returns. It is a common practice to consider the value effect by the classification of firms according to their fundamentals such as ratios on book-to-market, dividend yields, price-earnings, cash flow-price. Investors tend to overpay for growth firms that eventually fail to live up to expectation. The book-to-market approach has been extensively used on asset pricing models and is based on a self-financing strategy that yields positive abnormal risk-adjusted returns whenever valued firms outperform growth firms. Specifically, this strategy takes into account the opportunity that arises from the discrepancy between valued (firm fundamentals indicate a higher value than the traded one) and growth firms (investors' trading activity implies an overestimation of the value of the firm against its fundamentals). However, firms with high ratios of book-to-market value are typically those that have fallen on bad times. Thus, many researchers, including but not limited to DeBondt and Thaler (1987) claim that sorting portfolios on this fundamental (BMV) projects investors' overreaction to the market regime (bullish or bearish) and consequently, drives them to over-react resulting in high prices for growth firms and low for value firms. Finally, this process will yield low returns for the former group of securities and high returns for the latter.

The momentum effect was investigated extensively by Jegadeesh and Titman (1993) who formed portfolios on past performance, in a buy-and-hold framework, and imposed a selffinancing strategy for a period of time. Their findings were implemented in an asset pricing model by Carhart (1997) reinforcing thus the existence of a solid risk factor the sources of which can be found in behavioral finance. Indeed, the associated under-reaction and over-reaction of the momentum and return reversals could cause positive and negative autocorrelations on securities' returns.

4. Data and Research Methodology

This part of the analysis consists of three sections, the data set and the portfolio construction, the coherence of securities' returns and the development of multifactor asset pricing model. In the first part a detailed explanation of the row data used and of the portfolio construction is implemented. In the second part a simple metric is applied that accounts for the coherence of the data while in the last part a multifactor model is proposed that considers the asymmetric diversification benefits.

4.1 Data and Portfolio Construction

For the purposes of our analysis, data from the major US stock exchanges, the NYSE Euronext and the NASDAQ are used over three decades, spanning from 1980 to 2013. This period is characterized by volatile sub-periods, including Black Monday, the Asian and Russian crises, the Dot-com crash and the recent credit crisis, thus providing fertile ground for the exposition and development of asset pricing models. Moreover, data from the main US stock exchanges have been used extensively in the asset pricing literature due to the informational content of securities' prices; as such, the empirical findings of this paper aim to contribute to this discussion.

Throughout the examined sample period, a dynamic sample selection process is applied in order to control for survivorship bias. For each fiscal year the number of firms changes depending on the applied filtration scheme. On June of each fiscal year (t^*) the selected data consist of firms with available reported values during the previous fiscal year (t^*-1) . Weekly closing stock prices for each security and the 3-m Treasury Bill rates are used.

The different aspects of firm activity are proxied by the annually reported firm accounting data. Market capitalization is captured by firm's MV. Book-to-market value (BMV) expresses the way that expected growth of a firm's value is discounted on current prices. Momentum is formed according to the 12-month past performance.

Liquidity plays a pivotal role on asset pricing comprising a solid risk factor that comprises several aspects such as the transaction cost, the trading activity and the price impact. In our analysis we use the turnover ratio to proxy for the liquidity. Turnover ratio (TR) is defined as the ratio of the turnover by volume over the number of outstanding shares (VO/N). The turnover ratio accounts for the trading activity and is associated negatively with the investment holding period and the transaction cost. Amihud and Mendelson (1986) argued that less liquid assets are allocated to investors with longer investment horizons. In addition, Atkins and Dyl (1994) found a positive relationship between the average holding horizon and the spread. Since turnover ratio is the reciprocal of average holding period and is related to how quickly a dealer expects to turn around her position, the turnover ratio is also used as one of the liquidity measures. Datar, Naik and Radcliff (1998) used turnover ratio to measure liquidity, and concluded that turnover ratio is negatively related to expected asset returns.

Financial distress plays a significant role on the determination of asset returns. Campbell, Hilscher and Szilagyi (2011), among others, documents a default risk premium which is increased during recessions when investors' marginal utility is increased. In out paper, financial distress is proxied by the inverse interest rate coverage (Interest of Financial Expenses/EBITDA)and expresses a firm's interest expenses due to debt with respect to its earnings.

In each fiscal year, only firms with available reported values on this (analysis period) and the previous (formulation period) years are considered in the analysis. The last part of the filtration refers to thin trading. In each fiscal year, firms with no trading for four consecutive weeks and firms whose share price is less than \$5 are excluded from the sample.

This selection scheme forms the dataset upon which the analysis is based. Several portfolios are constructed on firm fundamentals associated with size, value, momentum, liquidity and financial distress. The market portfolio return at each week *t* during the current fiscal year (t^*) is defined as the value-weighted portfolio of all shares available in both the previous (t^*-1) and the current (t^*) fiscal year, while the weights are adjusted at the beginning of each fiscal period (which constitutes the end of the previous fiscal year):

$$r_{M,t,t^*} = \sum_{i=1}^{n_{fuscal year}} \sum_{i=1}^{t^*-1,t^*} \left(r_{i,t,t^*} \cdot W_{i, beginning of current fiscal year t^*} \right)$$
(8)

where $n_{fiscal year t^*-1,t^*}$ is the number of available firms during the previous (t^*-1) and current (t^*) fiscal year, r_{i,t,t^*} is the return of firm *i* at week *t* of the current fiscal year (t^*) , and $w_{i,beginning of current}$ fiscal year t^* is the weight of firm *i* at the current fiscal year (t^*) according to the value-weighted approach:

$$W_{i, beginnig of current fiscal year t^{*}} = \frac{\sum_{t=beginning of fiscal year t^{*}}^{t=end of fiscal year t^{*}} MV_{i,t} / (number of weeks during t^{*})}{\sum_{i=1}^{n_{fiscal year t^{*}-l,t^{*}}} \left[\sum_{t=beginning of fiscal year t^{*}}^{t=end of fiscal year t^{*}} MV_{i,t} / (number of weeks during t^{*})\right]}$$

$$(9)$$

The construction of the K factorson capitalization (SMB), value (HML), past performance (WML), liquidity (LIQ) and financial distress (FinDist) is based on a long-short self-financing portfolio strategy on the extreme portfolios with respect to the $(0-10^{\text{th}})$ and (90-100th) percentiles, as shown below:

$$r_{portfolio \ strategy \ k, t, t^*} = portfolio \ strategy_k \left(long \ portfolio_{t, t^*} - short \ portfolio_{t, t^*} \right)$$

$$r_{portfolio\ strategy\ k,t\ ,t\ }} = \sum_{i=1}^{n_{fuscal\ year\ i\ }^{*}-1,t\ ,i\ (long\ decile]}} \left(r_{i,t,t\ [long\ decile]} \times w_{i,beginning\ of\ current\ fiscal\ year\ t\ ,[long\ decile]}}\right) - \underset{\$\$}{\sum_{i=1}^{n_{fuscal\ year\ t\ }^{*}-1,t\ ,i\ (long\ decile]}} \left(r_{i,t,t\ [short\ decile]} \times w_{i,beginning\ of\ current\ fiscal\ year\ t\ ,[short\ decile]}}\right) - \underset{\$\$}{(10)}$$

Portfolios on fundamentals comprising the long-short strategy are formed during the fiscal year t^* -1, and, consequently, applied during fiscal year t^* .

^{§§}The size factor dictates an inverse strategy ([0-10]-[90-100] portfolio).

4.2 Inherent Diversification

The key point of modern portfolio theory is the coherence of securities' returns within a portfolio that serves diversification. Less symmetry within a portfolio implies a higher diversification benefit, with potential elimination of the idiosyncratic risk in relative terms. Consequently, for a portfolio with a specific number of shares (*n*), the existing interdependencies would alter the portfolio volatility dynamics. The simpler metric that accounts for these interdependencies is the correlation structure of the corresponding returns. The average correlation metric $\overline{\rho_{ij}}$ for a portfolio of n securities defined as the average of all non-diagonal elements of its correlation matrix:

$$\overline{\rho_{ij}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij}}{\frac{n}{2} \cdot (n-1)}$$

This metric is applied within the two $[0-10^{th}]$ and $[90-100^{th}]$ extreme portfolios, providing useful insights about the diversification asymmetries that are embedded in the imposed self-financing trading strategies:

$$\overline{\rho_{ij,t^*}^{[extreme \ decile]}} = \frac{\sum_{i=1}^{n_{fuscal \ year \ t^*-1, t^*, \ [extreme \ decile]}^{n_{fuscal \ year \ t^*-1, t^*, \ [extreme \ decile]}} \rho_{ij}}{\frac{n_{fuscal \ year \ t^*-1, t^*, \ [extreme \ decile]}}{2} \cdot \left(n_{fuscal \ year \ t^*-1, t^*, \ [extreme \ decile]} -1\right)}$$
(11)

The time series of the average pairwise correlation $\overline{\rho_{ij,t^*}^{[extreme decile]}}$ for each fiscal year would provide an indicator of the securities' inherent diversification evolution in each extreme portfolio. This metric would provide the necessary evidence enhancing thus, our motivation to adjust the yields of the long-short strategies in a way that eliminates potential asymmetry of the diversification benefits and the idiosyncratice risk as well.

4.3 Multifactor Models

In this paper, the investigation of the pricing mechanism of securities' returns is implemented by application of the conventional Fama and MacBeth (1977) model, adjusted to account for diversification asymmetries. In each fiscal year, t^* , portfolios consist of securities that are selected according to the filtration scheme. The quantification of the potential risk premia associated with firm fundamentals is derived through a two-stage process. First, through time series regressions, individual factor loadings are obtained (time series analysis); subsequently, the averaged individual returns are expressed a function of the estimated individual factor loadings for each fiscal period (cross-sectional analysis). This two-stage analysis determines the sign and the significance of the reward premium of each particular factor exposure (K factors), and the market risk premium.

The first step deals with the time series regressions for each fiscal year t^* (on a weekly basis):

$$E\left(r_{i,t,t^{*}} - r_{f,t}\right) = b_{0,i,t^{*}} + \sum_{k=1}^{K+1} b_{k,i,t^{*}} \cdot f_{k,t,t^{*}}$$

$$E\left(r_{i,t,t^{*}} - r_{f,t}\right) = b_{0,i,t^{*}} + b_{MRP,i,t^{*}} \cdot MRP_{t,t^{*}} + b_{SMB,i,t^{*}} \cdot SMB_{t,t^{*}} + b_{HML,i,t^{*}} \cdot HML_{t,t^{*}}$$

$$+ b_{WML,i,t^{*}} \cdot WML_{t,t^{*}} + b_{LIQ,i,t^{*}} \cdot LIQ_{t,t^{*}} + b_{FinDist,i,t^{*}} \cdot FinDist_{t,t^{*}}$$
(12)

where $f_{k,t}$ stands for the K+1 factors, including the market risk premium (MRP):

w . 1

$$MRP_{t,t^*} = r_{M,t,t^*} - r_{f,t} = \sum_{i=1}^{n_{fiscal year}} \left(r_{i,t,t^*} \cdot w_{i, beginning of current fiscal year t^*} \right) - r_{f,t}, \text{ where the weights are}$$

expressed with respect to market capitalization at the beginning of each fiscal year. The second step of the Fama-MacBeth regression corresponds to the cross-sectional averaging process with respect to firms; in each fiscal year t^* there are K+1 regressors (independent variables) with $n_{fiscal_year\ t^*-1,\ t^*}$ observations consisting of the estimated coefficients of the time series regressions b_{k,i,t^*} :

$$E_t\left(r_{i,t,t^*} - r_{f,t}\right) = a_{i,t^*} + \sum_{k=1}^{K+I} \lambda_{k,i,t^*} \cdot b_{k,i,t^*}$$

$$E_{t}\left(r_{i,t,t^{*}}-r_{f,t}\right) = a_{i,t^{*}} + \lambda_{MRP,i,t^{*}} \cdot b_{MRP,i,t^{*}} + \lambda_{SMB,i,t^{*}} \cdot b_{SMB,i,t^{*}} + \lambda_{HML,i,t^{*}} \cdot b_{HML,i,t^{*}} + \lambda_{WML,i,t^{*}} + \lambda_{UQ,i,t^{*}} \cdot b_{UQ,i,t^{*}} + \lambda_{FinDist,i,t^{*}} \cdot b_{FinDist,i,t^{*}}$$

$$(13)$$

The left side of the cross-sectional equation represents the average individual return with respect to time, i.e. averaging the returns of the 52 weeks for each of the $n_{fiscal year t^*-1,t^*}$ individual returns. This Simple Factor (SF) model constitutes the conventional methodology for the quantification of risk premia. The pricing mechanism of securities assumes a well-diversified portfolio scheme in the trading strategy imposed for each factor which is expected to reward investors only for the systematic component of the risk factor that they are exposed to.

However, this paper proposes the development of a multifactor model that aims to capture, in addition to the price of systematic risk, the residual price impact of potential asymmetries in idiosyncratic extreme portfolio undiversified risk. According to equations6 and 7, the diversification premium of each factor depends on the relevant asymmetry on the diversification benefits of its'constituents, i.e. the extreme portfolios that comprise the factor. Possible asymmetric diversification structures between the extreme portfolios within a stylized factor could generate spurious results dictating its sign, its magnitude and its statistical and economic significance. Thus, a new multifactor asset pricing model is proposed, the Diversification Risk Premium (DRP) model that incorporates this asymmetry in the form of a premium (π) in the time series and cross-sectional regressions of the conventional Fama-MacBeth model:

$$E\left(r_{i,t,t^{*}} - r_{f,t}\right) = b_{0,i,t^{*}} + \sum_{k=1}^{K+1} b_{k,i,t^{*}} \cdot f_{k,t,t^{*}} + \sum_{k=1}^{K+1} \delta_{k,i,t^{*}} \cdot \pi_{k,t,t^{*}}$$
(14)

$$E_{t}\left(r_{i,t,t^{*}}-r_{f,t}\right) = a_{i,t^{*}} + \sum_{k=1}^{K+1} \lambda_{k,i,t^{*}} \cdot b_{k,i,t^{*}} + \sum_{k=1}^{K+1} \lambda_{k,i,t^{*}} \cdot \delta_{k,i,t^{*}}$$
(15)

The first term of the equation accounts only for the systematic component of risk of the factor, while the second term, accounts for the asymmetries on the idiosyncratic risk of the factor according to equations 6 and 7. Thus, the DRP model is used to decompose the expected factor yields into their intrinsic and diversification premiumcomponents.

Investors should form their expectations about factor returns only on the basis of exposure to systematic risk. The magnitude, significance and interpretation of these expectations would depend on the relevant intrinsic component. A dominant intrinsic-value effect favors the existence of a risk factor. Rational investors experience returns on trading strategies, commensurate to the factors' systematic risk component.

However, when the diversification premium dictates a priced asymmetric effect on the idiosyncratic risk, the results obtained from a conventional multifactor model could mislead investors and market participants. This might be the case whenever the intrinsic value of the factor per se is not significant, but asymmetries on idiosyncratic risk command an additional expected return. The SF approach would then provide overestimates or underestimates of the expected returns. Specifically, a long position of a more asymmetric portfolio and a short position of a less asymmetric portfolio would impose an overestimation of the SF model factor effect. In contrast, a long position of the less asymmetric portfolio and a short one of a more asymmetric would result in an underestimation of the SF model factor effect.

5. Empirical Findings and Discussion

The results of this study are presented in three parts. Initially, the inherent risk and the risk-return profile of the portfolios are presented and subsequently, the inherent diversification within extreme portfolios is analyzed. Finally, the simple factor and the diversification risk premium multifactor models are analyzed in a comparative framework.

6.1 Risk-return Trade-off

Classification of firms according to market capitalization into small and big firms has very important implications. Small firms are individually riskier than big firms. According to Table 1 of the appendix, on average (for all firms and for all years), small firms' risk (3.819) is about 75% higher than that of big firms (2.252). In contrast, a portfolio consisting of small firms embeds lower risk (1.039) than one with big firms (1.172) by almost 13%. This means that

although individual small firms are riskier than big firms, the relative risk profile of the formed portfolios on size is higher for portfolios of big firms than that of small firms. Thus, historically, portfolios of smaller firms have the ability to absorb a larger portion of their risk, in contrast to portfolios of big firms. The greater ability of small firms to deflate their risk profile is attributed to their low correlation structure, which is 0.094, in contrast to 0.294of big firms. Classification of firms with respect to book-to-market ratio suggests that growth firms tend to be slightly riskier than value firms either individually or in portfolio context, without huge differences in the correlation structure of the extreme portfolios, which is 0.205 for the former and 0.150 for the latter. With regards to the momentum classification it seems thatlosers are slightly riskier than winners on an individual level, but less risky in a portfolio context, a fact that could be attributed to the lower correlation structure which is apparent within the losers' portfolio.Classification of firms according to illiquidity exhibits an asymmetry. While liquid and illiquid securities individually tend to have similar risk exposure, their portfolios comprise a higher diversification benefit for higher illiquidity (low TR) a fact that could be attributed to their lower correlation structure, i.e. 0.114 for illiquid and 0.263 for liquid securities. Finally, classification according to financialdistressdictates a higher risk profile for less distressed firms. Moreover, the neutral correlation structure effect, results in similar reduction of the risk profile in a portfolio-based structure.

Please insert Table 1 about here

A more comprehensive investigation of the relevant asset classes on size, value, momentum, liquidity and financial distress is presented in Table 2. The Sharpe ratio is presented for each asset class individually and on a portfolio context. These results reflect the aforementioned diversification asymmetries in terms of returns per unit of risk. The returns per unit of risk are increased, in absolute terms, in all asset classes when turning from individual securities to a portfolio context. However, for the case of the size and liquidity effects this change is substantial. While small firms' yield, turns from 0.234 to 0.859, for big firms, this turns from 0.213 to 0.409. Similarly, illiquid firms' yield, turns from -0.036 to -0.126, while for liquid firms', this turns from -0.031 to -0.065. Regarding the rest of the factors, the relative changes of the sharp ratio between their extreme portfolios does not change substantially.

Please insert Table 2 about here

Considering the inherent risk in security prices over time gives strong evidence of asymmetric responses of individual risk on a portfolio context with respect to the asset class of reference. Figure 4 illustrates the annual inherent risk of each asset class on an individual level and ina portfolio-based approach. Regarding the size classification, although the individual risk of small firms is greater than that of big firms throughout the investigated time period, it is observed that in a portfolio-based approach the opposite holds. Regarding the book-to-market classification, it is observed that value firms exhibit slightly lower risk than growth firms both on an individual level and ina portfolio-based approach. Classification of firms according to their historical performance (momentum) reveals a slightly greater volatility for losers compared to winners on an individual level, which shifts to the opposite effect when considered in a portfolio context. The liquidity dictates a similar risk profile for both deciles on an individual basis, which turns in favor to illiquid firms when using a portfolio context. Regarding financial distress, firms with low exposure toinverse interest coverage ratio seem to exhibit higher risk than distressed firms on an individual basis, while in a portfolio-based approach these differences fade out.

Please insert Figure 4 about here

Overall, although the risk-reward slopes are similar on an individual level for small and big firms, their portfolios show considerable divergence, with smaller firms ascribing a much greater slope. Classification of firms according to book-to-market produces negative average portfolio returns per unit of risk for growth firms and positive ones for value firms, in line with the strategy to sort the former and go long the latter. Value firms are less risky on an individual and portfolio level and less correlated from growth. The extreme value portfolio produces extraordinary positive rewards per unit of risk compared to negative rewards for growth firms.Although there are no substantial differences in the risk profiles of firms with different historical performance, a momentum effect takes place, dictating extraordinary gains per unit of risk for past winners. Moreover, the difference between past winners and past losers is slightly dampened in a portfolio-based approach, a shift that could be explained by the correlation asymmetries benefiting the losers.Turning to liquidity, in spite of relatively similar individual average risk profiles between illiquid (low TR) and liquid (high TR) stocks, portfolios of illiquid shares exhibit a higher sharp ratio, in absolute terms. Nevertheless, illiquid portfolios might be able to recoup a portion of the return deficit on a fully-diversified basis, due to their lowinherent correlation structure. Finally, financially distressed firms register, higher portfolio returns per unit of risk, but, counter-intuitively, lower risk both individually and in a portfolio-based context. This observation combined with the neutral correlation asymmetry in the corresponding extreme portfolios casts doubts on the inherent risk-return profile of strategies based on financial distress. A crucial question that arises at this point is whether the source of these cross-sectional divergences could be traced to the systematic component of inherent risk of asset classes and/or the diversification asymmetries within them.

6.2 Inherent Diversification

When considering the inherent diversification in security prices, intertemporally, there is strong evidence of asymmetric effects on the coherence of firms' returns within extreme portfolios on several firm fundamentals and through time. The inherent diversification is proxied through the average pairwise correlation ($\overline{\rho_{ij,t^*}^{[extreme decile]}}$). Figure 5 illustrates the average correlation for the extreme portfolios of each firm fundamental over time, resulting to seven subfigures. These figures also depict the corresponding correlation structure of all securities, thus providing a benchmark for our discussion while also illustrating the available number of firms based on the filtration scheme applied at each fiscal year. Classification of firms according to size and liquidity exhibits the higher diversification asymmetry between the corresponding extreme portfolios. The discrepancy on the coherence within these portfolios tends to become stronger as the number of firms increases throughout the examined time period, strengthening their economic importance since they do not depend on the portfolio size. Another useful insight derived from this figure is that the correlation dynamics within all firms for each fiscal year does not contain a symmetric reference with respect to the coherence that is taking place within extreme portfolios. This is apparent obvious for the capitalization and the liquidity effects, where small and illiquid firms undoubtedly diverge from the norm that the market imposes. The remaining firm fundamentals do not involve such asymmetries, at least on average, though there exist specific periods of time for which they exhibit short term asymmetries. For example, when considering the book-to-market and the momentum characteristics during the 2000-2003 period (Dot.com crisis), or the financial distress and the momentum during the period 1992-1993 (Gulf war), it is obvious that discrepancies between the extreme portfolios' inherent diversification exist thoughin the short term.

Please insert Figures 5 about here

6.3 Multifactor Models

This part of the analysis refers to the simple factor (SF) and the diversification risk premium (DRP) multifactor models within the Fama-MacBeth cross-sectional framework. Table 3 presents the estimation results of the SF model while Table 4 those of theDPEusing the equally-weighted portfolio approach, intertemporally. The estimated coefficients represent the risk premia associated with market portfolio and firm fundamentals, i.e. size, value, momentum, liquidity and financial distress according to equations 13 (SF) and 15 (DRP). The estimated results are presented for each fiscal year and for the whole parameter set, accommodating the level of statistical significance of the whole parameter set. Specifically, in the case of the DRP model, each factor's effect is decomposed in to two components, the intrinsic value that accounts for the systematic risk exposure on the factor and the diversification risk premium which is associated with the asymmetry of the coherence within the factor and accounts for asymmetries in the idiosyncratic risk exposure. For illustrative purposes the estimated risk premia for both model approaches, SF and DRP, are shown in Figure 6 in addition to the numerical values that are presented in Tables 3 and 4. This figure contains seven sub-figures accounting for the alphas, the market risk premium and the risk premia of the examined effects, such as size, value, momentum, liquidity and financial distress. The estimations of each subfigure refer to the SF and DRP models and a comparative analysis is straightforward. Furthermore, while significances (at 5%) are denoted by the main solid lines of each subfigure, the actual estimations irrelevant of their significance are also presented by the dashed lines shedding more light about the trends irrespective of significance.

Please insert Table 3 about here

Please insert Table 4 about here

Please insert Figure 6 about here

Regarding the SF model, the alpha intercept (fist sub-figure of Figure 6) seems to be significantly positive during the period of 1985-1986, on 2004, on 2007, during 2010-2011 and on 2013. However, this is negative on 1984, on 1987, during 2001-2003 and 2008-2009. The market risk premium (second sub-figure of Figure 6) is significant and positive on 1997, during 2002-2003, 2008-2009 and 2011-2012. Negative premia are observed, however, on 2000. The SMB strategy (third sub-figure of Figure 6) provides positive yields on 1995, during 2000-2001, on 2009 and on 2012. Contrarily, the size effect comprises a negative premium for the period 1996-1999, during 2005-2006 and during 2010-2011. The HMLstrategy (fourth sub-figure of Figure 6) exhibits a positive significant presence during 1987-1988, 1992-1994, 1997-1998 and 2001-2003. Negative premia are obtained during 1999-2000 and 2008-2009. Investors trading on momentum (fifth sub-figure of Figure 6), obtain positive returns during 1985-1986, on 2000, 2002, during 2005-2008, on 2011 and 2013. However, the WML strategy has failed on 1987, during 1996-1997 and especially on 2001 with great loses, during 2008-2010 and on 2012. Trading on illiquidity (sixth sub-figure of Figure 6) rewards investors with positive returns on 1996 and 1998 and during the period 2001-2002, 2008-2009 and 2012-2013. However, this strategy creates loses during 1985-1987, 1994-1995 and especially during 1999-2000 and during 2010-2011. Finally, financial distressed firms (seventh sub-figure of Figure 6) provide greater returns from non-distressed firms during 1992-1993, 1997-1998 and especially during 2001-2002, on 2005, on 2007 and during 2010-2012. The opposite holds only during the period 1999-2000 and 2008-2009. Overall, one could argue that almost all of the factors exhibit qualitatively a similar pattern which is characterized by negative premia non- tranquil periods and positive ones otherwise. For instance, at the beginning of the dot.com crisis the market and the associated risk factors have declined significantly in order to reform to positive regimes later on, a fact that is translated in negative alphas. Similarly, the recent crisis has affected all these factors negatively, leading to negative alphas.

Results obtained from the DPE model exhibit several differences with respect to the significance and the magnitude of the risk premia. The size effect (third sub-figure of Figure

6) decomposes into its intrinsic value and the associated diversification premium. Overall, the intrinsic component of the size effect exhibits lower yields, in absolute terms, than the one provided by the SF model. Moreover, on 1991, a qualitatively different yield exists between the intrinsic component of SMB according to the DRP and the SF models. Finally, on 2008 the DRP model suggests that the size effect is priced, in contrast to the SF model which does not price it.With regards to the value effect, its intrinsic value (DRP model) is similar to the one suggested by the SF model. A difference, however, is apparent on 2005 and on 2012 where according to the DRP, the systematic component of risk of the HML should reward investors, in contrast to the SF model.A strategy on the momentum of the 12-month past performance according to the proposed DRP consists of an intrinsic value during 1991-1992 and a negative yield on 1998, contrary to the SF model's expectation. However, it is shown from the fifth sub-figure of Figure 6, that the intrinsic value is slightly greater, in absolute terms, than that of the SF model. The long-short strategy on liquidity is priced differently in the proposed DRP model and in the conventional SF model. Specifically the intrinsic value is priced during 1988-1990 and 1992-1993 in contrast to the premium that the SF model expects. Overall, the intrinsic premium of liquidity is lower than that suggested by the SF model. Furthermore, the financial distress premium comprises an intrinsicvalue on 2008 in contrast to the SF model. The SF model provides overestimations during the dot.com crisis and underestimations during the recent financial crisis compared to the intrinsic component of financial distress premium in the proposed DRP model. Finally, alphas in both specifications tend to be positively significant during tranquil periods and negatively significant in volatile periods of time. The significance of alphas in both models, underlines the importance of the misspecification issues accommodated in multifactor asset pricing models based on size, value, momentum, liquidity and financial distress, though in a short period of time.

Overall, it could be argued that a conventional approach, such as the SF model, would provide overestimations or underestimations of the intrinsic component of the risk premium depending on the coherence of the long-short extreme portfolios. These spurious results diminish the risk-return trade-off, calling into question the market's informational efficiency. In the case of the size and liquidity factors, the long position exhibits lower correlations resulting to a positive diversification risk premium and consequently to an overestimation of the SF approach. In contrast, the trading on momentum would impose a long position on highly correlated securities and a short one on securities with less coherence, resulting to a negative diversification risk premium and consequently to an underestimation of the SF approach. The rest of the factors (value and financial distress) do not exhibit substantial differences with respect to the premia suggested by the SF and the DRP models.

The proposed DPE model controls for asymmetries and reward investors only for the systematic component of risk. Potential asymmetries of idiosyncratic risk could be controlled in the formulation of the long-short portfolio strategies, though this would entail a mean-variance optimum portfolio construction.

Another important finding stems from the average correlations within the market portfolio. Figure 6, and for each sub-figure, shows the average pairwise correlation of the market portfolio's securities (dashed blue line). During periods of market stress, such as Black Monday, the Gulf War, the Asian Crisis, the Dot.com crisis and the recent credit crisis, there is evidence of tighter relationships between securities' returns. Not only are potential extreme portfolio diversification asymmetries associated with risk premia (significance and magnitude), but there also exists a time varying pattern, conditional on the market regime of the examined stock exchanges. The overall average pairwise correlation of constituent securities' returns plays a key role in the determination of the factor risk premia in the applied models. Overall, conventional SF and proposed DRPmodels' significant risk premia are associated with low intra-securities' correlations. More specifically, during periods of low correlation, the opportunities to generate positive alphas through the examined self-financing factor strategies increase.

6. Robustness Check

In order to enhance the importance and the consistency of the DRP model, a set of alternative methodological issues are incorporated in the analysisas a robustness check. These issues can be summarized in that a) the coherence of asset returns in examined through a regression analysis, b) the adoption of alternative percentiles for forming the extreme portfolios, c) the use of hierarchical regressions and d) the adoption of the value-weighted approach on the formulation of portfolios.

Firstly, following Campbell, Lettau, Malkiel and Xu (2001), a qualitatively equivalent metric to average correlation is provided by the average coefficient of determination \overline{R}^2 of the following regression: $E(r_{i,t,t^*}) = \gamma_{0,i} + \gamma_{1,i} \cdot r_{t,t^*, portfolio of n shares}$ (16)

The deterministic coefficient of this regression (R^2) expresses the portion of the dependent variable's variability over the independent's variability (Regression Sum of Squares). A low average deterministic coefficient $(\overline{R_{i,t^*,[extreme decile]}^2})$ would imply a weaker relationship, imposing a low coherence within the portfolio. In our analysis the average deterministic coefficient, similarly to the average pairwise correlation, is estimated within the $[0-10^{th}]$ and $[90-100^{th}]$ extreme portfolios as an additional check for the embedded diversification asymmetries:

$$E(r_{i,t,t^*}) = \gamma_{0,i} + \gamma_{1,i} \cdot r_{t,t^*, \text{ extreme portfolio on } k^{th} \text{ firm fundamental}}, \qquad \overline{R_{i,t^*,[extreme decile]}^2}$$
(17)

The average deterministic coefficient for each extreme portfolio of the examined factors is estimated intertemporaly and illustrated in Figure 7 of the appendix. This figure consists of five sub-figures to express the dependencies with the extreme portfolios for the examined factors, i.e.size, value, momentum, liquidity and financial distress. Undoubtedly, the figures provide evidence consistent with the prior analysis, that is, the size and the liquidity effects exhibit asymmetries in the coherence between the formed extreme portfolios.

Secondly, the extreme portfolio strategies are formed on the basis of the 30^{th} and 50^{th} percentiles (i.e. $[0-30^{th}]$ vs. $[70^{th}-100^{th}]$ and $[0-50^{th}]$ vs. $[50^{th}-100^{th}]$) instead of the 10^{th} percentiles (i.e. $[0-10^{th}]$ vs. $[90^{th}-100^{th}]$). These percentiles aim to consider more convenient portfolio schemes that account for most of the firms involved in each fiscal year. The empirical findings do not change qualitatively with that of the extant analysis on the decile extreme portfolios. For parsimonious reasons the results are not presented in the appendix, but are available upon request.

Thirdly, the analysis is implemented on an hierarchical way comprising five models. The first model incorporates the three factor model, i.e. MRP, size and value, while the second, the third and the fourth models incorporate in addition to the three factors, the momentum, the

liquidity and the financial distress effects, respectively. Finally, the fifth model consists of all of the examined factors including the MRP. For parsimonious reasons the results are not presented analytically, but comprehensively in Table 5 of the appendix. Table 5 refers to the 10% percentile averaged risk premia for the SF and the DRP hierarchically. The market risk premium ranges from 7% to 10% on an annual basis. As regards to the size effect, apparently, the SF model provides overestimations of the intrinsic value. Within the Fama and French formulation, which is expressed in model 1, the size effect dies out when the diversification risk premium is considered. In the subsequent models that consider the other factors as well (momentum, liquidity and financial distress), the size effect is very weak and apparently its intrinsic value turns to negative. As regards to the value effect this provides a solid risk premium in all model specifications which is similar within the SF and DRP approaches. Thus, investors are expected to be rewarded with a 4% premium irrelevant of the diversification risk premium. The conventional (SF) momentum factor, in the second model, is greater than its intrinsic value and vice versa in the case of the fifth model. The first finding could be attributed to the higher average correlation which is apparent to the portfolio that we buy than the one which we shortsell. Furthermore, the liquidity effect is overestimated on the SF model with respect to the intrinsic value. According to this strategy investors hold a long position on less correlated securities and a short one on higher correlated shares, comprising thus a positive diversification risk premium. Finally, the financial distress effect comprises a solid risk premium, almost 3% on an annual basis, for all models and irrelevantly of the diversification risk premium.

Please insert Table 5 about here

Finally, the whole analysis is implemented by consideration of the value-weighted portfolio approach. The empirical findings, which are not presented for parsimonious reason, lead to similar conclusions for all model specifications and for all of the three used percentiles, i.e. 10%, 30% and 50% percentile.

7. Conclusion

This paper analyzes the limitations of multifactor asset pricing models, which embed often factor idiosyncratic risk on their expectations, and proposes an adjustment, the Diversification Risk Premium model, to overcome this misspecification issue.

Many stylized financial facts that are documented as market anomalies could be priced in a multifactor framework. The cornerstone of asset pricing models lies on that rational risk averter investors expect to be rewarded only for the systematic component of risk of the factors that they are exposured to, since they hold well-diversified portfolioseliminating thus the associated idiosyncratic component of risk.

A common way to form strategies on firm fundamentals (stylized facts) is the adoption of a self-financing portfolio strategy, according to which investors hold undervalued and short sell overvalued securities. This implies a long position on a portfolio consisting of undervalued securities and a short one on a portfolio consisting of overvalued ones. Firm fundamentals are used to account for several characteristics, such as size, value, liquidity and financial distress. The extreme portfolios consist only of the securities that correspond to the upper or the lower percentile range with respect to the relevant firm fundamental. Thus, the extreme portfolios undoubtedly embed a portion of idiosyncratic risk which cannot be fully eliminated. Consequently, the implementation of self-financing strategies raises many questions on whether the two components are comparable in terms of the inherent diversification ability.

Utilizing a simple metric of securities' coherence, there is strong evidence of significant asymmetries on the ability of portfolios on specific asset classes to absorb idiosyncratic risk. Motivated by the asymmetric on the diversification benefits between the long-short portfolios we propose the Diversification Risk Premium multifactor model that estimates the intrinsic value of each factor of the model.

According to the empirical findings, the presence of asymmetries on the coherence of securities' returns across the size and liquidity factors, diminishes their statistical and economic significance. The value and financial distress factors do exhibit asymmetric effects and it is found that they reward investors significantly irrelevantly of the diversification risk premium.

Finally, it is found that during periods of market stress, the coherence of securities' returns is increased and the associated risk factors diminish. This implies that historically, risk premia are associated with low intra-securities' correlations.

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List of Tables

Table 1. Variance and Correlation Dynamics of Extreme Portfolios

Average Risk and Correlation

This table presents the on average individual and portfolio risk and the correlation structure of the extreme portfolios on firm fundamentals on an annual basis. The lower extreme portfolio corresponds to the [0-10] and the upper to the [90-100] percentile. Individual risk is expressed by the realized standard deviation, while average correlation is calculated as the average pairwise correlation within each extreme portfolios.

fundamental	$\overline{\sigma}_{i,0-10}$	$\overline{\sigma}_{p,0-10}$	$\overline{\sigma}_{\scriptscriptstyle i,0\text{-}10}/\overline{\sigma}_{\scriptscriptstyle p,0\text{-}10}$	$\overline{\sigma}_{i,90-100}$	$\overline{\sigma}_{ ext{p,90-100}}$	$\overline{\sigma}_{i,90\text{-}100}/\overline{\sigma}_{p,90\text{-}100}$	corr _{ij,0–10}	<i>corr</i> _{ij,90–100}
SMB	3.819	1.039	3.674	2.252	1.172	1.922	0.094	0.294
HML	3.633	1.484	2.448	3.336	1.142	2.922	0.205	0.150
WML	4.149	1.534	2.705	3.673	1.640	2.240	0.165	0.217
LIQ	3.605	1.014	3.554	3.384	1.643	2.061	0.114	0.263
FinDist	4.042	1.503	2.690	3.080	1.266	2.432	0.174	0.194

Table 2. Sharpe Ratio of Extreme Portfolios

Average Return and Sharpe ratio

This table presents the on average individual and portfolio Sharpe ratio of the extreme portfolios on firm fundamentals on an annual basis. The lower extreme portfolio corresponds to the [0-10] and the upper to the [90-100] percentile.

fundamental	$\overline{SR}_{i,0-10}$	$\overline{SR}_{p,0-10}$	$\overline{SR}_{i,90-100}$	$\overline{SR}_{p,90-100}$
SMB	0.234	0.859	0.213	0.409
HML	-0.112	-0.273	0.340	0.995
WML	-0.122	-0.330	0.312	0.700
LIQ	-0.036	-0.126	-0.031	-0.065
FinDist	-0.013	-0.035	0.199	0.485

Simple Factor model (SF) rit = alpha + beta MRP + bs SMB + bh HML + bw WML + bl LIQ + bfd FinDist																				
This is the cross sectional regression of the Fama-MacBeth framework. The coefficients correspond to the annualized premium awarded for trading the EW long-short strategy (10% extreme portfolios) on firm fundamentals. EW																				
													factors	с	rM	SMB	HML	WML	LIQ	FinDist
													coeff	-22.346 ***		10.659 ***		-15.861	-0.732	7.023 **
1982	p-value	0.000	0.484	0.005	0.000	0.000	0.851	0.043												
1983	coeff	53.689 ***	-2.649 ***	12.657 …	-5.770 *	-0.663	-15.014	4.798												
	p-value	0.000	0.003	0.001	0.054	0.858	0.000	0.110												
1984	coeff	-44.166 ***				-21.727	3.116	1.391												
	p-value coeff	0.000 16.902 ····	0.000 10.883	0.364 -6.776 ***	0.000 9.539 ····	0.000 16.857 ····	0.222 -4.977 ····	0.586 8.009 ····												
1985	p-value	0.000	0.585	0.004	0.000	0.000	0.009	0.001												
1986	coeff	19.556	4.751	-2.638	3.737 **	25.229	-10.198	7.192												
1980	p-value	0.000	0.192	0.217	0.036	0.000	0.000	0.000												
1987	coeff	-5.963 ***	-8.669	-15.665 ***	3.776 **	-12.818	-12.621	-3.069 **												
	p•value	0.001	0.788	0.000	0.028	0.000	0.000	0.022												
1988	coeff	-10.861	-3.414	-2.411	6.533	0.228	-0.797	1.008												
	p-value coeff	0.009 -1.492	0.615 16.599	0.260 -1.930	0.000 3.157	0.907 -7.244 ····	0.562 -0.465	0.480 4.031 **												
1989	p-value	0.000	0.123	0.335	0.111	0.000	0.805	0.016												
1000	coeff	-16.122 *	7.649	-2.858	-12.335	1.432	1.361	-6.380 ***												
1990	p-value	0.066	0.126	0.212	0.000	0.514	0.432	0.001												
1991	coeff	-3.169	-1.734	-6.574 …	-3.172 *	9.796 …	-1.065	0.862												
	p-value	0.253	0.876	0.001	0.065	0.000	0.499	0.501												
1992	coeff	7.169	-9.874 **	-4.345 **	5.816	7.835	-1.652	7.491 …												
	p-value coeff	0.498 14.198	0.040 -0.140 **	0.043 -0.630	0.003 11.224	0.000 -0.831	0.395 0.611	0.000 13.804 ····												
1993	p-value	0.000	0.041	0.746	0.000	0.601	0.738	0.000												
1004	coeff	-9.737	-1.924	-0.141	4.295	1.298	-5.752	1.828												
1994	p-value	0.000	0.156	0.923	0.002	0.359	0.000	0.148												
1995	coeff	12.602 ***	1.798	9.302 ***	-3.336 **	3.174 **	-7.079	-4.656 ***												
	p-value	0.000	0.135	0.000	0.016	0.024	0.000	0.002												
1996	coeff	6.190	22.557	-3.168 **	-1.118	-3.899 **	10.126	-0.886												
	p-value coeff	0.000 9.314 ····	0.007 33 244 ····	0.044 -17.756 ***	0.277 17 520 ····	0.039 -15.514 ***	0.000 0.685	0.522 15.216 ***												
1997	p-value	0.000	0.001	0.000	0.000	0.000	0.635	0.000												
1998	coeff	15.331 ***	9.744	-9.565 ***	4.530	0.334	10.621	9.449 …												
1550	p-value	0.000	0.398	0.000	0.000	0.735	0.000	0.000												
1999	coeff	-11.628 ***	-4.716	-13.862 ***	-5.991 …	6.175 …	-5.223	-2.886 ***												
	p-value	0.000	0.336	0.000	0.000	0.000	0.000	0.000												
2000	coeff	-0.201 ***	-35.490 ***	23.683 ····	-12.727 ***	0.000	-19.438 ····	-25.242 ***												
	coeff	4.830	36.196			-54.774 ***	29.361	41.944 ***												
2001	p-value	0.000	0.000	0.001	0.000	0.000	0.000	0.000												
2002	coeff	-29.486 ***	47.298	25.387	34.630	40.388	27.956	32.008 ***												
2002	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000												
2003	coeff	-7.336 ***	27.049 ***		-4.100	-1.584	0.261	-2.537 ***												
	p-value	0.000	0.000	0.121	0.000	0.184	0.777	0.000												
2004	coeff	18.077 ····	20.076 0.654	-1.308 0.133	1.374 ** 0.042	-1.084 ** 0.028	-0.209 0.809	3.868 ····												
	coeff	0.997	12.094 **	-4.554	8.400	7.467 ***	-1.989	8.862 ***												
2005	p-value	0.000	0.015	0.000	0.000	0.000	0.004	0.000												
2006	coeff	0.487	-7.694 •	-3.610 ***	-0.677	8.017	-3.747	-1.796 ***												
2000	p-value	0.000	0.052	0.000	0.217	0.000	0.000	0.000												
2007	coeff	10.836 …	5.988	-3.700 ***	3.226	2.386 ***	0.870	4.029 ***												
	p-value	0.000	0.303	0.000	0.000	0.000 5.508 ····	0.196	0.000 -14.469 ***												
2008	coeff	-53.061 ····	13.194 ···	1.994 * 0.069	-6.779 ····	0.000	0.000 ····	0.000												
	coeff	-31.296 *	24.750 ***			-12.522		-13.813												
2009	p-value	0.014	0.000	0.000	0.000	0.000	0.000	0.000												
2010	coeff	12.983	2.138		-0.727		-10.803	3.665 ***												
2010	p-value	0.000	0.125	0.000	0.298	0.000	0.000	0.000												
2011	coeff	27.645 …	4.930 ***			14.519		2.029 ***												
	p-value	0.000 11 266	0.000	0.000	0.000	0.000	0.000	0.000 1 577												
2012		-11.366 ***			1.204 *	-7.033 ***	15.157	1.577 ***												
	p-value coeff	12.707	10.269	-0.319	-2.234	7.773 ····	-5.177 ***	-0.979 **												
2013	p-value	0.000	0.627	0.646	0.000	0.000	0.000	0.047												
	p-value coeff	0.000 12.707 ····	0.000 10.269	0.000 -0.319	0.092 -2.234 ***	0.000 7.773 ····	0.000 -5.177 ***	0.00 -0.9												

Table 4.Diversification Risk Premium: Fama-MacBeth Risk Premia

Diversification Risk Premium model (DRP) rit = alpha + beta MRP + bs SMB_intr + bs' SMB_π + bh HML_intr + bh' HML_π + bw WML_intr + bw' WML_π + bl LIQ_intr + bl' LIQ_π + bfd FinDist_intr + bd' FinDist_π													
This is the cross sectional regression of the Fama-MacBeth framework. The coefficients correspond to the annualized premium awarded for trading the EW long-short strategy (10% extreme portfolios) on firm fundamentals. EW													
	factors	с	rM	SMB_in	SMB_π	HML_in	HML_π	WML_in	WML_π	LIQ_in	LIQ_π F	inDist_inF	inDist_
1982	coeff	-3.345	-22.918	8.924 **	-1.761	20.484 ***	-18.949	-17.300 ***	3.458	-2.692	10.700 ***	6.289 *	12.908
	p-value	0.001	0.308	0.018	0.525	0.000	0.000	0.000	0.329	0.481	0.000	0.065	0.000
1983	coeff	57.511 ····	0.009	0.006	0.003	· -5.240 ·	-2.099 0.513	-2.433 0.507	-18.591 ····	-15.374 ····	6.691 ····	6.644 ** 0.025	-2.690
		-31.867	30.241 ***		6.694		0.885	-20.461***		2.624	2.252	0.491	-6.819
1984	p-value	0.759	0.000	0.505	0.000	0.000	0.711	0.000	0.000	0.298	0.146	0.851	0.024
1985	coeff	23.599	17.416	-6.322	2.527	8.754 🚥	0.313	15.831	-17.399	-5.460	0.984	8.148 ***	-0.408
1903	p-value	0.000	0.571	0.005	0.107	0.000	0.882	0.000	0.000	0.004	0.474	0.001	0.828
1986	coeff	28.277		-2.766	-0.653	3.800 **	2.786		-14.349 …		2.296 **	6.784 …	-3.251
	p-value	0.000	0.115	0.198	0.636	0.035	0.207	0.000	0.000	0.000	0.045	0.001	0.122
1987	coeff	2.245 0.918	-2.737 0.630	-15.596 *** 0.000	6.122 ····	* 3.244 * 0.064	-1.381 0.470	-12.533 ····	-1.581 0.510	-12.606 *** 0.000	3.560 ····	-3.241 **	-1.252 0.238
	coeff	-3.062	8.169	-2.472	4.573		3.460 **		1.522	-0.463	2.581 ***	1.368	0.238
1988	p-value	0.361	0.441	0.246	0.000	0.000	0.018	0.858	0.249	0.733	0.010	0.329	0.453
1989	coeff	6.253	27.195 *	-1.878	2.343	3.080	1.716	-6.915	0.961	0.192	4.124 …	4.632 ***	-4.293
1909	p-value	0.000	0.074	0.345	0.119	0.121	0.299	0.000	0.627	0.919	0.001	0.006	0.005
1990	coeff	-4.321	19.130	-4.553 **	6.950 …	-12.992 ***	15.628	1.371	4.842 **	0.311	8.074 …	-8.519 ***	6.272
	p-value	0.002	0.116	0.039	0.000	0.000	0.000	0.516	0.041	0.852	0.000	0.000	0.000
1991	coeff	8.949 **		-5.939			5.145 …		-2.123	-2.697 *	1.796	0.938	-1.381
	p-value coeff	0.012 12.473 **	0.484 -2.520 *	0.002 -3.944 *	0.000 -1.189	0.117 3.862 **	0.000 -6.975 ***	0.000 7.862 ····	0.150 -2.899 *	0.095 -1.027	0.102 2.563 **	0.460 5.537 ***	0.248 -0 470
1992	p-value	0.013	0.066	0.060	0.309	0.048	0.000	0.000	0.060	0.587	0.020	0.003	0.742
1993	coeff	17.664		-0.759	1.242	11.478	-5.071 **		-1.685	0.237	3.125 **	13.491	
1993	p-value	0.000	0.080	0.697	0.366	0.000	0.026	0.739	0.306	0.897	0.032	0.000	0.000
1994	coeff	-7.093 *	0.596	-0.075	-0.470	4.461 …	-1.310	1.415	-1.382	-5.819	3.249 ***	1.943	-0.044
	p-value	0.025	0.165	0.959	0.651	0.001	0.477	0.321	0.449	0.000	0.009	0.126	0.978
1995	coeff	20.154		9.778 ***			5.969 ***		-1.563	-6.719	4.279 ***		7.687
	p-value coeff	0.000 8.306 ····	0.178 26.878 ***	0.000 -2.524	0.000 2.823 **	0.035 -0.965	0.000 -0.093	0.012 -4.251 **	0.221 6.292 ····	0.000 10.603	0.001 -4.156 ***	0.008 -1.032	0.000 -0.472
1996	p-value	0.000	0.002	0.115	0.011	0.351	0.937	0.026	0.008	0.000	0.002	0.458	0.703
	coeff	14.485		-17.878 ***		17.469		-15.435 ***	4.169	0.501	-1.548	15.217	
1997	p-value	0.000	0.001	0.000	0.000	0.000	0.033	0.000	0.001	0.730	0.288	0.000	0.071
1998	coeff	21.394 …	14.379	-9.380 ***	6.537 …	5.253 …	1.328	0.893	-6.259 …	10.862	-1.607	9.874 …	-7.258
	p-value	0.000	0.287	0.000	0.000	0.000	0.229	0.366	0.000	0.000	0.293	0.000	0.000
1999	coeff	-5.021	3.628	-13.198 ***			8.036 ***		-20.484 ***	-6.145	9.433 ***	2.101	
	p-value coeff	0.639 5.726 ····	0.219 -29.715 ***	0.000	0.000	0.000 • -12.947 •••	0.000 -3 /191 ***	0.000 21.143 ····	0.000 -8 33/1 ····	0.000 -20.091 ***	0.000 10.962 ***	0.003	0.000 9.818
2000	p-value	0.000	0.003	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000
	coeff		41.674	5.086		51.532		-55.116	4.292 **	29.500		42.006 ***	
2001	p-value	0.000	0.000	0.000	0.565	0.000	0.003	0.000	0.031	0.000	0.000	0.000	0.000
2002	coeff	-27.676	57.039 ***	24.836	-8.631	34.348 ***	11.092 ***	41.788	-25.642 ***	27.628	8.015 ***	31.270	-8.384
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2003	coeff	-4.505 ***	29.104 ***	0.633	3.847 😁	-3.963 ***	1.439	-0.593	7.113 🚥	-0.368	2.809 ***	-2.019 ***	6.193
	p-value	0.000 16.814 ***	0.000 20 333	0.536	0.000 -0.002	0.000	0.282 -0.089	0.617	0.000 -0.313	0.687	0.002	0.001 4.252 ····	0.000
2004	p-value	0.000	20.333 0.428	-1.691 * 0.051	-0.002 0.996	1.171 * 0.083	-0.089 0.925	-0.959 * 0.051	0.673	-0.298 0.730	-0.489 0.459	0.000	-2.780
	coeff		15.217 **	-4.874			-0.612	7.687	-1.155	-2.812	1.386 **	8.450	
2005	p-value	0.000	0.026	0.000	0.001	0.000	0.304	0.000	0.102	0.000	0.038	0.000	0.000
2006	coeff	1.995	-4.346	-3.437 ***	-0.285	-0.356	-5.204 ***	7.426 ***	-5.874 ····	-2.948	-6.217 ***	-0.763	-1.435
	p-value	0.239	0.131	0.000	0.573	0.512	0.000	0.000	0.000	0.000	0.000	0.129	0.077
2007	coeff	17.690		-4.089 ***	1.981 …		1.814 **		-4.813	-0.407	-1.712 **	3.513	
	p-value coeff	0.000	0.042 10.956 ***	0.000	0.000 7.612 ···	0.000	0.012	0.009 8 / 10 ····	0.000	0.545	0.038	0.000	0.000
2008	p-value	-33.285 ····	0.000	-0.851 0.427	7.612 ····	· -8.853 ····	0.000 ····	0.000	-10.944 ····	-1.282 0.186	0.000	-14.716 *** 0.000	0.000
		-29.295	28.233	8.355 ***	4.020			-13.066 ***	-6.164		1.221	-12.850 ***	
2009	p-value	0.721	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.198	0.000	0.000
2010	coeff	12.232	3.145	-11.809 ***	3.123		-2.060 *	-6.980		-10.546		3.690 ***	2.011
-010	p-value	0.000	0.199	0.000	0.000	0.327	0.052	0.000	0.000	0.000	0.003	0.000	0.001
2011	coeff	25.471		-6.236	0.127	-8.815	6.847	14.313	-3.263	-13.847	0.000	1.991 ***	5.296
	p-value	0.000	0.002	0.000	0.790	0.000	0.000	0.000	0.000	0.000	1000	0.000	0.000
2012	coeff	-9.801						-5.797 🚥				1.445 ***	
	p-value	0.000	0.000 8.659	0.000	0.000	0.501	0.000 1.611 #	0.000	0.000	0.000 -6 29 4	0.002	0.000	0.000
2013	coeff	16.920	8.659	-0.345	-0.901 **	-1.978 ***	1.611 **	7.404 ***	-3.861 ***	-6.294 ***	-0.488	-0.822 *	-0.136

Table 5. Hierarchical models with the Averaged Risk Premia

This is the averaged result of the cross sectional of the Fama-MacBeth regression over the whole time period. The estimated coefficients correspond to the annualized premium awarded for trading the EW long-short strategy (10% extreme portfolios) on firm fundamentals over the time period of examination. The insignificant coefficients through time are set to zero on the averaging process.

		alpha	MRP	SMB	HML	WML	LIQ	FIN.DISTR
				EW				
model 1	SF	-0.843	7.578	0.295	3.831			
model I	DRP	1.891	7.864	0.035	3.558			
model 2	SF	-0.843	8.483	0.327	3.852	0.461		
moderz	DRP	1.457	9.204	-0.212	3.765	0.427		
model 3	SF	-0.588	7.791	0.011	4.258		0.439	
model 5	DRP	0.130	8.494	-0.172	3.962		-0.231	
model 4	SF	1.350	5.201	-0.315	3.514			2.765
model 4	DRP	3.509	5.877	-0.331	3.440			2.863
model 5	SF	-0.550	6.798	-0.024	3.995	0.457	-0.153	2.776
model 5	DRP	6.990	10.014	-0.230	3.829	0.585	-0.491	2.934

model 1 rit = alpha + beta MRP + bs SMB_intr + bs' SMB_ π + bh HML_intr + bh' HML_ π

model 2 rit = alpha + beta MRP + bs SMB_intr + bs' SMB_ π + bh HML_intr + bh' HML_ π + bmom WML_intr + bmom' WML_ π

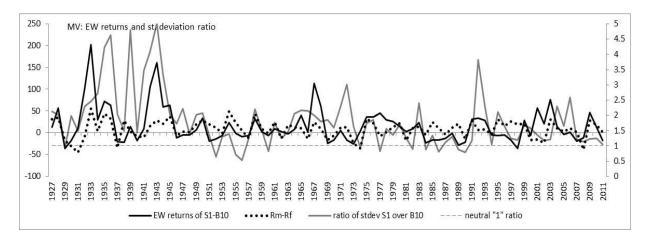
model 4 rit = alpha + beta MRP + bs SMB_intr + bs' SMB_ π + bh HML_intr + bh' HML_ π + bfd FinDist_intr + bfd' FinDist_ π

rit = alpha + beta MRP + bs SMB_intr + bs' SMB_ π + bh HML_intr + bh' HML_ π + **model 5** bmom WML_intr + bmom' WML_ π + bl LIQ_intr + bl' LIQ_ π + bfd FinDist_intr + bfd' FinDist π

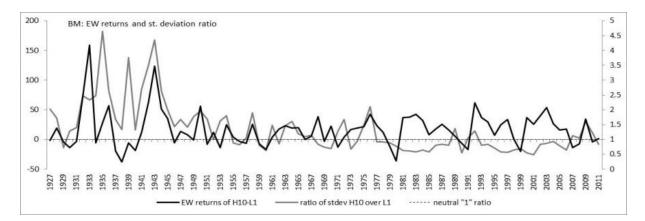
List of Figures

Figure 1.Risk and return of self-financing strategies on MV, BMV and momentum. Data Library K.R. French<u>http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html</u>

First sub-figure: SMB



Second sub-figure: HML



Third sub-figure: WML

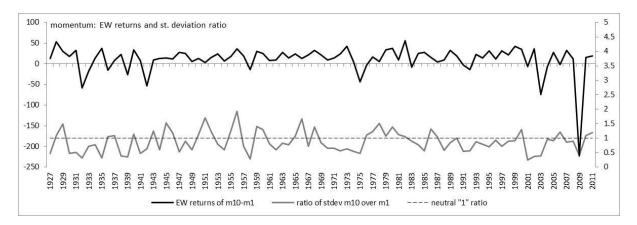
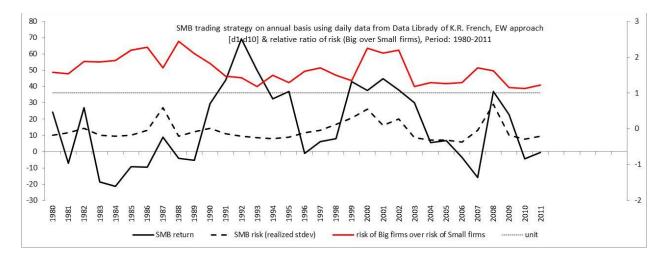


Figure 2. F&F, Size and Value/Growth Effect, Fama and French data, period: 1980-2011 These subfigures are based on K.R. French's data library and refer to the realized volatility of small and big firms and of growth and valued firms on an annual frequency. Data Library K.R. French<u>http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html</u>

First sub-figure: SMB



Second sub-figure: HML

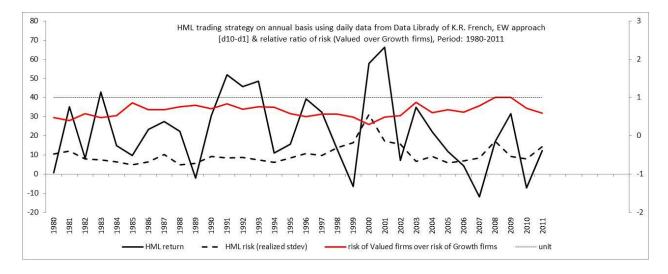
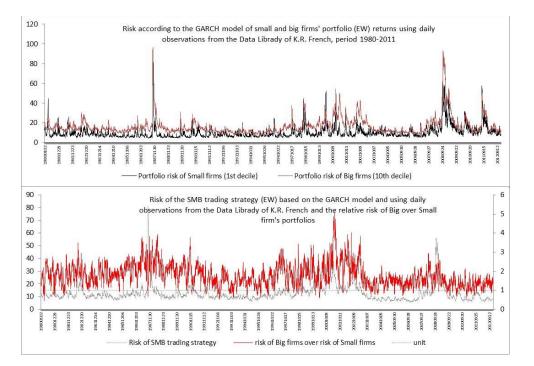


Figure 3. F&F, Volatility of extreme portfolios on MV and BMV

These subfigures are based on K.R. French's data library and refer to the GARCH volatility of small and big firms and of growth and valued firms on a daily frequency. Data Library K.R. French<u>http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html</u>

First sub-figure: SMB



Second sub-figure: HML

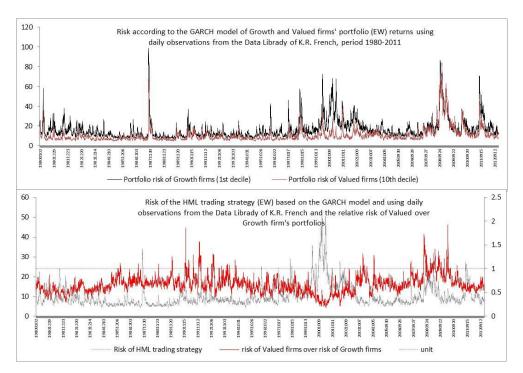
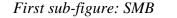
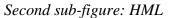
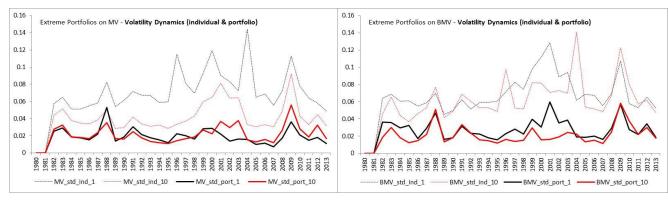


Figure 4. Volatility Dynamics within extreme portfolios

These figures illustrate the representative individual risk (on average) and the portfolio risk for each asset class (extreme portfolio).

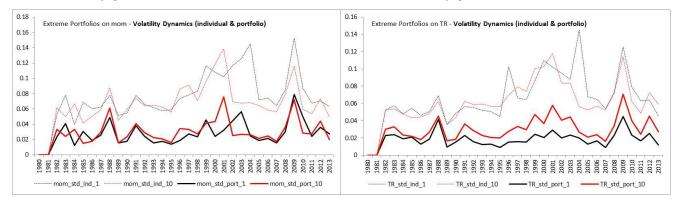






Third sub-figure: WML

Fourth sub-figure: LIQ



Fifth sub-figure: FinDist

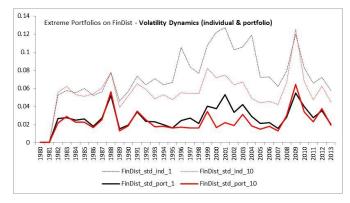
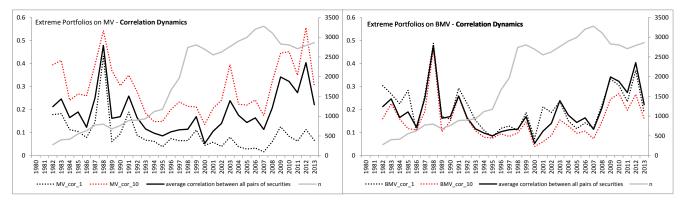


Figure 5. Correlation Dynamics within the extreme portfolios of trading strategies

These figures illustrate the average pairwise correlation $\overline{\rho_{ij,t^*}^{[extreme \ decile]}}$ within extreme portfolios.

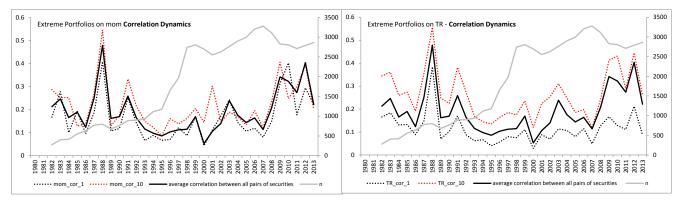
First sub-figure: SMB

Second sub-figure: HML



Third sub-figure: WML

Fourth sub-figure: LIQ



Fifth sub-figure: FinDist

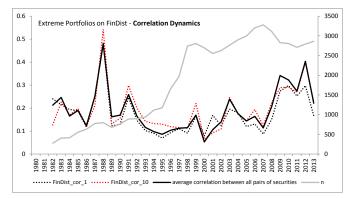
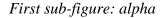
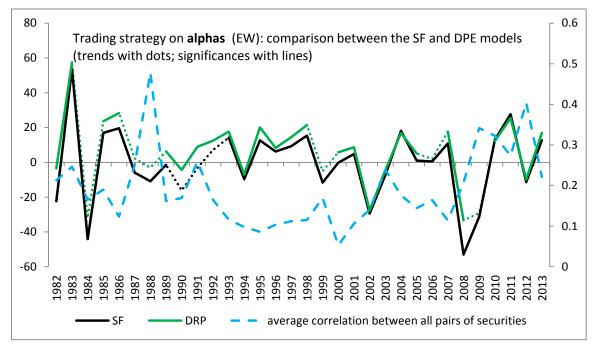


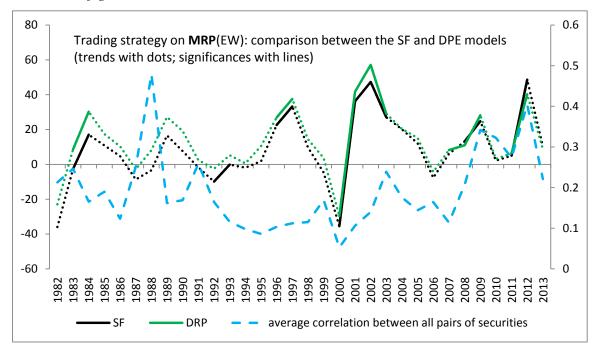
Figure 6. Risk premia estimation based on the SF and the DPE models

These figures illustrate the risk premia of the SF and the DPE models. The significant values of the risk premia are represented by the solid line, while their values for the whole time period are denoted with dashed lines.

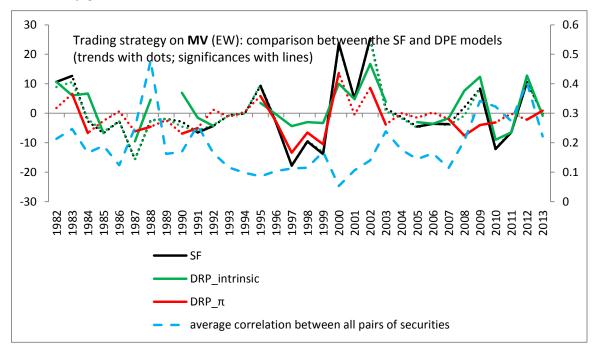




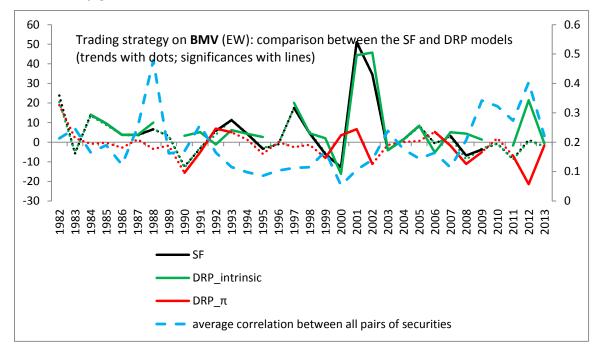
Second sub-figure: MRP



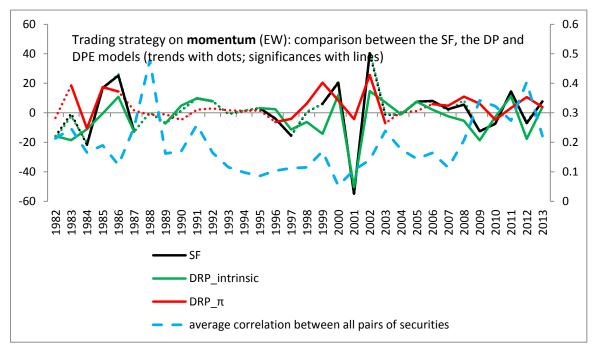
Third sub-figure: SMB



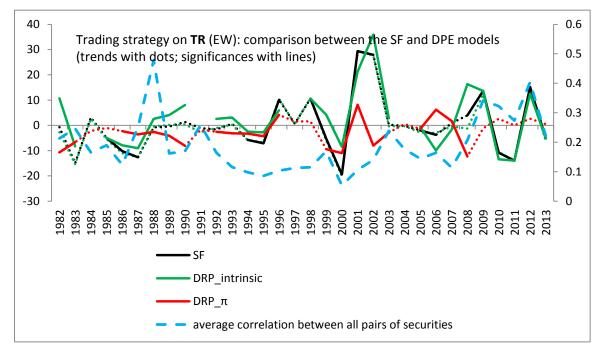
Fourth sub-figure: HML

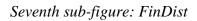


Fifth sub-figure: WML



Sixth sub-figure: LIQ





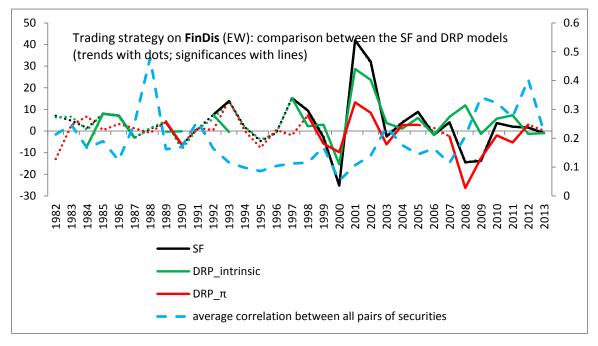
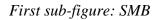
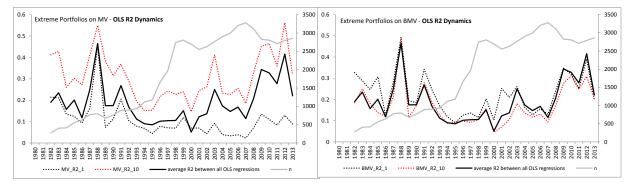


Figure 7. Average deterministic coefficient (OLS R²) within extreme portfolios

These figures illustrate the average deterministic coefficient $\overline{R_{i,t^*,[extreme \ decile]}^2}$ of the regressions within extreme portfolios.

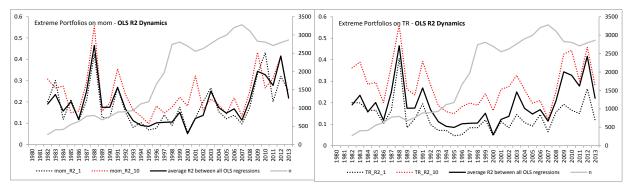


Second sub-figure: HML



Third sub-figure: WML

Fourth sub-figure: LIQ



Fifth sub-figure: FinDist

