Behavioral Mispricing Factors in Europe: Pricing Tests and Fund Performance Attribution

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Abstract

We validate the behavioral pricing model in the European equity markets and assess whether these mispricing factors are exploited by European equity funds. Using the long-horizon financing (FIN) and the short-horizon post–earnings announcement drift (PEAD), we find that both behavioral mispricing factors are present in Europe. However, European equity funds do not exploit these opportunities symmetrically, excluding short-horizon portfolio adjustments based on event-driven earnings announcements.

Keywords: Long-horizon behavioral mispricing; Short-horizon behavioral mispricing; European equity markets; European equity funds.

1 Introduction

The modern behavioral asset pricing literature consistently documents that security prices exhibit predictable return patterns that cannot be fully explained by traditional risk-based models. Seminal contributions such as (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999; Barberis & Thaler, 2003) highlight the role of investor overconfidence, representativeness, limited attention, and slow information diffusion in generating persistent mispricing. Within this framework, Daniel et al. (2020) propose a parsimonious three-factor model, hereafter DHS model, consisting of the market factor, a financing-based mispricing factor (FIN) and a post-earnings announcement drift factor (PEAD). They show that DHS model explains a substantial share of the cross-sectional variation in U.S. stock returns and performs competitively against leading risk-based benchmarks such as Fama & French (1993, 2015) and Carhart (1997).

The FIN factor captures valuation errors related to corporate issuance and repurchase decisions, and is consistent with the broader evidence that corporate financing activity can be associated with subsequent return patterns that are hard to reconcile with purely risk-based explanations (e.g., Barberis & Thaler, 2003; Daniel et al., 1998). The PEAD factor reflects the systematic underreaction to earnings news, one of the most robust anomalies in asset pricing (Ball & Brown, 1968; Bernard & Thomas, 1989), and is consistent with models of gradual information diffusion and limited attention (Hong & Stein, 1999; Barberis & Thaler, 2003). Recent reviews emphasize that the PEAD factor lacks a single comprehensive explanation, with proposed mechanisms ranging from trading frictions to explicitly behavioral channels (Fink, 2021). Consistent with a behavioral interpretation, underreaction-related anomalies are systematically stronger in settings where attention is plausibly low and limits to arbitrage are more binding, suggesting that the speed of information diffusion and the capacity of arbitrage capital jointly shape the magnitude and persistence of post-news drift (Chen et al., 2023).

The modern asset pricing landscape is characterized by a "factor zoo" in which many proposed factors appear statistically significant, but are often sensitive to construction choices, sample design, and benchmark selection. This creates nontrivial model uncertainty and complicates the interpretation of abnormal performance and mispricing-based return predictability (Hou et al., 2019). In this factor zoo environment, disciplined justification on specific mispricing dimensions is particularly relevant. Recent research integrates or selects among competing factor models rather than treating any single specification as definitive. Chib et al. (2024) make Bayesian model comparisons to highlight that, among a large candidate set of predictors, PEAD and FIN are consistently supported as core factors alongside canonical benchmarks such as market and momentum factors.

Despite the growing relevance of DHS model, empirical validation outside the U.S. remains scarce. Large-scale international evidence questions the assumption of anomaly-based results established in the U.S. for other institutional environments (Cakici et al., 2024). Hollstein (2022) finds that local factor models can dominate regional or global alternatives when explaining cross-sectional patterns, underscoring the importance of region-tailored validation. These considerations make out-of-U.S. sample validation completely necessary for an appropriate use of FIN and PEAD factors in other markets, and Europe is a particularly important laboratory in this regard. While Europe in aggregate holds one of the largest shares of equity market capitalization in the world after the U.S. (WFE, 2025), it differs markedly from the U.S. equity markets in institutional features that may amplify or dampen mispricing, including heterogeneous ownership structures, legal and governance frameworks, and the increasing prominence of ESG regulation and disclosure (La Porta et al., 1998; Faccio & Lang, 2002; Christensen et al., 2021). The increasing divergence in pricing between U.S. and European equities (ESMA, 2025a) suggests that this different market structure may affect the speed and completeness with which information is incorporated into prices, implying that the magnitude and persistence of mispricing could differ materially in Europe. Validation of the DHS model in Europe is therefore essential both to assess its cross-market replicability and to understand its practical relevance for investors and asset managers operating outside the U.S.

The implications of this research gap for the European asset management industry are particularly relevant given that the European mutual fund industry is one of the largest and most heavily regulated asset management ecosystems (EFAMA, 2025) and has significant economic relevance worldwide (ICI, 2025). The literature shows that fund managers may load on return-driving characteristics and factors either intentionally or unintentionally (Kacperczyk et al., 2005; Barber et al., 2016; Berk & van Binsbergen, 2015). Moreover, regulatory constraints, style mandates, ESG policies, market frictions and career concerns may limit managers' ability to exploit mispricing (Pástor & Stambaugh, 2002; Cremers et al., 2013; Amihud & Goyenko, 2013; Hartzmark & Sussman, 2019). Furthermore, fund flows may not efficiently reward managers who successfully exploit mispricing, particularly if such skills do not translate into simple performance metrics that drive investor attention (Evans & Sun, 2021).

To the best of our knowledge, no study has systematically examined European fund exposure to FIN and PEAD, nor the role these exposures play in shaping fund performance. We address this dual question in this paper. First, we evaluate whether FIN and PEAD are significantly priced in Europe by replicating these DHS factors across a broad European equity universe and applying canonical asset pricing tests, including the GRS test (Gibbons et al., 1989), Fama–MacBeth regressions, and pricing error analysis. This validation allows us to assess whether the DHS model keeps the explanatory power in European markets relative to standard benchmarks such as Fama & French (2015) or Carhart (1997), as Daniel et al. (2020) obtained in the U.S.

Our empirical validation reveals that the behavioral framework of Daniel et al. (2020) provides a powerful and parsimonious description of European equity returns. We find that both the financing (FIN) and post-earnings-announcement drift (PEAD) factors earn significant premia that are not subsumed by traditional risk factors. Notably, the PEAD effect in Europe appears even more pronounced than in the original U.S. study, exhibiting a higher Sharpe ratio and remarkable statistical robustness in cross-sectional tests. While the FIN factor provides unique explanatory power in time-series spanning tests—consistent with the U.S. evidence—its unconditional price of risk in the European cross-section is less pervasive than that of PEAD, suggesting that earnings-related underreaction is a more dominant driver of mispricing in this region. Overall, the behavioral model substantially enhances the investment opportunity set relative to conventional production-based models, confirming that the psychological mechanisms identified by Daniel et al. (2020) for the U.S. market are not only present but potentially more influential in the institutional landscape of European equity markets.

Second, we examine the exposure of European equity funds to FIN and PEAD factors using time-series beta estimates and measures of dynamic factor exposure. We investigate whether managers actively exploit mispricing opportunities, display patterns consistent with behavioral biases such as overconfidence or return chasing, and whether ESG constraints, or stated investment style condition their ability to benefit from these opportunities. Finally, we assess whether exposure to FIN and PEAD translates into superior risk-adjusted performance, contributing to the debate on managerial skill.

A key implication of our framework is that exploiting mispricing may not show up as residual alpha once FIN and PEAD are explicitly included in the model. In traditional specifications such as Fama & French (1993) or Carhart (1997), the return associated with financing- and earnings-related mispricing can often appear as unexplained performance, potentially leading to higher estimated alpha. However, when controlling for FIN and PEAD, the portion of returns attributable to these sources of mispricing can shift from the intercept to the factor loadings, which can mechanically reduce residual alpha. In that case, a lower alpha should not be interpreted as evidence of no skill. Instead, when managers are able to identify these patterns and maintain systematic exposure to profitable mispricing factors, that management pattern can be viewed as a distinct dimension of managerial skill more closely related to factor allocation than to pure stock selection (Berk & van Binsbergen, 2015; Kacperczyk et al., 2005; Daniel et al., 2020). This is a key distinction for interpreting fund performance in the presence of mispricing-based factors.

Although European equity funds exhibit heterogeneous exposure to DHS behavioral factors, a considerable percentage reports significantly negative exposure to long-term FIN factor, indicating systematic tilts toward intensive issuer firms relative to low-issuance firms. Our evidence also supports that portfolios' systematic exposure to short-horizon earnings-underreaction factor (PEAD) is residual in the European equity fund industry. This result is consistent with the limitations to short-term portfolio adjustments based on event-driven earnings announcements. Our analysis further provides evidence that behavioral factors, mainly long-horizon mispricing, make a significantly positive contribution to European equity fund returns. Fund managers obtain returns through systematic exposure to behavioral mispricing, not solely through risk exposures to standard factors or stock-picking skills.

Our findings offer a unified view of mispricing in European equity markets and its relevance for mutual fund managers, investors, and market supervisors, contributing to a deeper understanding of how value is generated in the European fund industry. For fund managers, validation of the FIN and PEAD factors in Europe suggests that systematic exposure to financing- and earnings-related mispricing represents a significant source of returns beyond traditional risk premia. Managers should recognize that exploiting these anomalies constitutes a distinct dimension of skill that may not be fully captured by conventional alpha metrics, underscoring the importance of incorporating behavioral factors into performance attribution frameworks and investment processes. For investors, our results highlight the need to reassess how fund performance is evaluated. Traditional alpha estimates that do not control for behavioral mispricing factors may overstate managers' skills, while funds with lower alphas under mispricing-adjusted models may still demonstrate valuable factor allocation abilities. Investors should therefore demand more granular performance attribution that distinguishes between residual alpha and factor-based returns, enabling more informed capital allocation decisions. For market supervisors, the presence of significant mispricing in European equity markets raises questions about market efficiency and investor protection. Regulatory initiatives aimed at enhancing disclosure quality may help to mitigate these anomalies. Supervisors should consider whether existing fund disclosure requirements adequately inform investors about exposures to mispricing factors, as these may carry distinct risk-return profiles that differ from traditional factor exposures.

The remainder of this paper is organized as follows. Section 2 validates the DHS model in the European equity markets. Section 3 includes the application of the DHS model to the European equity fund industry. Finally, section 4 concludes.

2 Asset pricing tests for the DHS model in the European equity markets

European equity markets exhibit distinct institutional characteristics that differentiate them from the U.S. and potentially lead to different magnitudes of equity mispricing. These European features include varied ownership concentration patterns, divergent legal traditions, and corporate governance systems, and a more pronounced regulatory emphasis on environmental, social, and governance (ESG) pillars than in the U.S.

La Porta et al. (1998) shows that legal origin plays a critical role in shaping equity market development and investor protection across countries. Their seminal study of 49 countries reveals that common law countries, predominantly the U.S. and U.K., generally provide the strongest legal protections for investors, while French civil law countries offer the weakest protections, with German and Scandinavian civil law systems falling in between. This legal taxonomy has significant implications for the development of European equity markets, as European equity markets with weaker investor protections exhibit higher ownership concentration and less developed capital markets, as rational investors demand larger stakes to compensate for the increased risk of lower levels of protection of their rights. This heterogeneous legal landscape across European equity markets contrasts sharply with the uniform common law foundation that supports equity markets throughout the U.S.

European corporate ownership structures differ significantly from the dispersed ownership model typical of U.S. public companies. Faccio & Lang (2002) examine 5,232 corporations across 13 Western European countries, finding that while 36.93% are widely held, 44.29% are family-controlled, with substantial cross-country variation. Widely-held firms dominate in common law countries like the U.K. and Ireland, while family control prevails in continental Europe, particularly in Italy, France, Germany, and Spain, where minority shareholder protections are weaker. Unlike the U.S., where conflicts arise between dispersed shareholders and managers, European markets face conflicts between controlling shareholders and minority investors. Faccio & Lang (2002) document that controlling shareholders frequently employ dual-class shares, pyramidal structures, and cross-holdings to enhance control beyond their cash flow rights. These mechanisms potentially exacerbate agency problems and misaligning interests between controlling and minority shareholders. These ownership structures in the European equity markets affect market liquidity, information asymmetry, and minority shareholder risks, factors that can influence asset pricing and market efficiency.

The regulatory approach to environmental, social, and governance (ESG) dimensions is also a critical distinction between European and U.S. equity markets. Europe has emerged as a global leader in mandating corporate sustainability disclosure, while the U.S. has historically maintained a voluntary approach. The European Union's Non-Financial Reporting Directive (NFRD 2014/95/EU), effective in 2017, does not have a direct parallel in U.S. securities regulation, where ESG disclosure remains largely voluntary under general materiality principles. The European approach works with the "double materiality" principle, requiring companies to disclose both how sustainability issues affect financial performance and how the firm's activities impact society and the environment. This stakeholder-oriented view contrasts with the shareholder-primacy model dominating U.S. corporate law. The NFRD explicitly aims to "drive change" in corporate sustainability practices, using transparency to incentivize desirable behavior—differing from the U.S. focus on providing material information for investment decisions without shaping corporate behavior toward broader social objectives. These divergent approaches may have significant equity market implications. European firms face higher compliance costs and more extensive ESG disclosure obligations, potentially affecting their cost of capital and competitive positioning. However, mandatory disclosure may reduce information asymmetry and improve comparability, potentially enhancing market efficiency. Christensen et al. (2021) note that mandatory sustainability reporting can have effects on capital markets (through changes in firm value, cost of capital, and investor portfolio allocations), on stakeholders other than investors (including employees, customers, and communities), and on firm behavior itself (through real effects on corporate policies and activities). The EU's Corporate Sustainability Reporting Directive (CSRD) further expands reporting requirements through detailed European Sustainability Reporting Standards (ESRS), suggesting the regulatory gap between European and U.S. markets may widen, with implications for cross-border capital flows, listing decisions, and market attraction for different investor types.

These institutional differences, including but not only limited to legal principles, ownership structures, and ESG regulation, between Europe and the U.S. create distinct market environments that may differentially affect the extent and nature of equity mispricing. The weaker legal protections and higher ownership concentration in continental European markets may reduce the disciplining effect of capital markets on corporate management, potentially allowing mispricing to persist longer than in more liquid, widely-held U.S. markets. Conversely, the presence of large, informed controlling shareholders in European firms may reduce information asymmetry for certain types of information, potentially improving pricing efficiency along some dimensions. The mandatory ESG disclosure regime in Europe provides a richer information environment regarding sustainability matters, which may enhance the ability of investors to price ESG-related risks and opportunities, though the effectiveness of this disclosure depends critically on enforcement mechanisms and the quality of reported information. The validation of the DHS model for the European equity markets will help to understand how these institutional differences act as mechanisms that potentially generate or correct mispricing across distinct market structures.

2.1 The DHS behavioral asset pricing model

The institutional features of European equity markets discussed above shape the information environment, trading frictions, and agency conflicts faced by investors. These mechanisms are central to the empirical relevance of mispricing-based asset pricing frameworks, because they affect both (i) the speed at which valuation errors are corrected through arbitrage and (ii) the types of information that are incorporated into prices.

In this context, we validate the DHS behavioral asset pricing model in European equities. The DHS framework posits that a small set of behavioral factors, constructed from mispricing-related firm-level signals, captures systematic return variation associated with investor underreaction and overreaction across short and long horizons. We estimate the DHS specification by augmenting the market factor with two behavioral factors designed to capture mispricing at different horizons:

$$r_{p,t} = \alpha_p + \beta_{m,p}\, Mkt_t + \beta_{FIN,p}\, FIN_t + \beta_{PEAD,p}\, PEAD_t + e_{p,t}, \tag{1}$$

where $r_{p,t}$ is the euro excess return on portfolio p in month t, computed relative to the one-month German government yield, Mkt_t is the market excess return, FIN_t is the financing factor, and $PEAD_t$ is the post-earnings-announcement drift factor. The intercept α_p measures abnormal performance and $e_{p,t}$ is a zero-mean residual.

2.1.1 The FIN factor

The FIN factor proxies for long-horizon mispricing related to firms' financing activity. Its construction combines the five-year composite share issuance (CSI) of Daniel & Titman (2006) and the one-year net share issuance (NSI) of Pontiff & Woodgate (2008). The CSI measure captures the five-year growth in market equity not attributable to stock returns:

$$CSI_{i,t} = \ln\left(\frac{ME_{i,t}}{ME_{i,t-5}}\right) - r_{i,(t-5,t)}, \tag{2}$$

where, for CSI measured in June of year t, $ME_{i,t}$ is firm i's market equity at end-June of year t, $ME_{i,t-5}$ is market equity at end-June of year $t-5$, and $r_{i,(t-5,t)}$ is the cumulative log return from end-June $t-5$ to end-June t.

The NSI measure is defined analogously over a one-year horizon excluding cash dividends:

$$NSI_{i,t} = \ln\left(\frac{ME_{i,t}}{ME_{i,t-1}}\right) - r_{i,(t-1,t)}. \tag{3}$$

At the end of each June, firms are assigned to Small (S) or Big (B) using the June median market-equity breakpoint. Independently, firms are assigned to Low (L), Middle (M), or High (H) financing groups using an index formed from the NSI and CSI rankings with the 20th and 80th percentiles as breakpoints. Firms classified as high (low) by both rankings—or high (low) by one ranking while missing the other—are assigned to H (L); all remaining firms are assigned to M. This yields six value-weighted portfolios (SL, SM, SH, BL, BM, BH), held from July of year t to June of year $t+1$ and rebalanced annually. The FIN factor is defined as:

$$FIN_t = \frac{1}{2}(R_{SL,t} + R_{BL,t}) - \frac{1}{2}(R_{SH,t} + R_{BH,t}), \tag{4}$$

that is, the average return on low-issuance portfolios minus the average return on high-issuance portfolios.

2.1.2 The PEAD factor

The $PEAD$ factor captures short-horizon mispricing associated with delayed price adjustment to earnings news. Following Chan et al. (1996), the earnings-news signal is measured by the four-day cumulative abnormal return around the most recent earnings announcement:

$$CAR_i = \sum_{d=-2}^{1} (R_{i,d} - R_{m,d}), \tag{5}$$

where $R_{i,d}$ is stock i's return on day d and $R_{m,d}$ is the market return on day d, both measured relative to the announcement date. To form the PEAD portfolios, firms are sorted on CAR from the most recent announcement; firms are excluded if no earnings are announced in the past six months.

At the beginning of month t, firms are assigned to S or B using the median market-equity breakpoint. Independently, firms are assigned to Low (L), Middle (M), or High (H) earnings-surprise groups using the 20th and 80th percentiles of CAR_i measured at the end of month $t-1$. The six intersection portfolios are value-weighted for month t. The $PEAD$ factor is defined as:

$$PEAD_t = \frac{1}{2}(R_{SH,t} + R_{BH,t}) - \frac{1}{2}(R_{SL,t} + R_{BL,t}). \tag{6}$$

These DHS factors are designed using European equities and European accounting and market data. We rely on Badía et al. (2026), who build FIN and $PEAD$ using firms from 22 European Union countries: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.[1] The construction uses the entire LSEG universe and includes both active and inactive stocks to mitigate survivorship concerns.[2] Accordingly, our tests do not rely on importing U.S.-estimated behavioral factors; instead, we evaluate whether Europe-specific DHS factors exhibit economically meaningful premia and contribute to explaining the returns of European test portfolios.

Our empirical validation proceeds in four steps. First, we document summary statistics and factor performance to establish the basic distributional properties and economic magnitude of the DHS factor returns. Second, we examine the correlation structure and model-level Sharpe ratios (Sharpe, 1992) to assess comovement across DHS factors and the mean–variance implications of the factor set. Third, we run spanning tests for behavioral factors to evaluate whether the DHS factors add incremental investment opportunities beyond alternative factor specifications. Fourth, we conduct cross-sectional tests via Fama–MacBeth regressions to assess whether exposures to the DHS factors are priced in the European cross-section.

2.2 Summary statistics and factor performance

Table 1 reports summary statistics for the monthly returns of all factors over the sample period. Besides the DHS behavioral factors constructed for European equities, we also include the Fama–French risk factors augmented with momentum (FF+MOM) as a standard benchmark.[3] This allows us to (i) gauge the economic magnitude of the DHS premia relative to widely used risk factors, and (ii) assess whether DHS factors provide incremental explanatory power and investment opportunities beyond conventional factor models.

The average excess market return is 0.53% per month, with a standard deviation of 5.38% and a Sharpe ratio of 0.099. These values are broadly in line with long-run evidence for developed equity markets (e.g. Fama & French, 1993; Fama & French, 2015), though the sample period, which spans both the global financial crisis and the European sovereign debt crisis, is relatively volatile.

The performance of the behavioral factors is remarkable. The FIN factor delivers an

[1]The sample contains no firms from Cyprus, Croatia, Latvia, Lithuania, or Malta because LSEG does not provide sufficient information for these countries.

[2]In Badía et al. (2026), the mispricing factors are constructed from LSEG-ESG-covered stocks in the countries listed above, spanning 1,332 firms from January 2004 to December 2022 (228 months).

[3]The Fama–French and Carhart factors were obtained from Kenneth French's data library and converted from USD to EUR following the currency-conversion procedure of Glück et al. (2021).

Table 1: Descriptive statistics of monthly factor returns

Factor	Mean (%)	Std. Dev. (%)	t-statistic	Sharpe ratio
MKT	0.53	5.38	1.54	0.099
FIN	0.45	1.68	4.13	0.266
PEAD	0.99	1.53	10.02	0.647
SMB	0.12	1.79	1.05	0.068
HML	0.02	2.64	0.13	0.009
RMW	0.34	1.55	3.36	0.217
CMA	0.00	1.50	0.00	0.000
MOM	0.74	3.63	3.16	0.204

Notes: This table reports descriptive statistics for monthly factor returns from January 2004 to December 2023 (240 observations). MKT is the market excess return over the risk-free rate. FIN is the long-horizon issuance and repurchase factor, and PEAD is the post–earnings-announcement drift factor constructed following Daniel et al. (2020). SMB, HML, RMW, CMA, and MOM are the standard Fama–French size, value, profitability, investment, and momentum factors. Means and standard deviations are in percent per month. The t–statistic is the time–series t–test of mean equal to zero. The Sharpe ratio is the mean divided by the standard deviation.

average return of 0.45% per month with a standard deviation of 1.68%, yielding a Sharpe ratio of 0.266 with a t–statistic of 4.13%, which is close to the Sharpe ratio of 0.20 obtained for the U.S. equity market (Daniel et al., 2020). The PEAD factor performs even more strongly: its average return is 0.99% per month with a volatility of 1.53% and a Sharpe ratio of 0.647, highly statistically significant with a t–statistic of 10.02. For comparison, Daniel et al. (2020) report a Sharpe ratio of roughly 0.35 for the U.S. PEAD factor. Our results therefore indicate that the earnings underreaction effect is, if anything, more pronounced in European equities over this period. Among the traditional factors, SMB and HML have economically small and statistically insignificant means (0.12% and 0.02% per month, respectively), consistent with the mixed international evidence on size and value premia (see, e.g., Fama & French, 2012). By contrast, RMW and MOM show significant premia: RMW has an average return of 0.34% per month (Sharpe 0.217, $t = 3.36$) and MOM returns 0.74% per month (Sharpe 0.204, $t = 3.16$), consistent with the findings on profitability and momentum by Novy & Marx (2013) and Jegadeesh & Titman (1993). The investment factor CMA is essentially flat over this sample. Overall, Table 1 shows that both behavioral factors FIN and PEAD earn sizeable and highly significant premia in Europe, comparable to or exceeding those of the strongest traditional factors. This already suggests that these behavioral dimensions are economically important in European markets, and motivates a closer comparison with standard multifactor models.

2.3 Correlation structure and model-level Sharpe ratios

Table 2 reports the correlation matrix of the factor returns. The FIN factor is moderately negatively correlated with the market ($\rho = -0.429$) and SMB ($\rho = -0.408$), and positively correlated with CMA ($\rho = 0.408$). This pattern is intuitive: firms engaging in net equity issuance tend to be larger, less risky, and more asset–heavy, and the FIN factor effectively goes long on equity repurchasers and short on net issuers. The correlation with CMA also reflects that high investment firms, which contribute to the short leg of FIN, tend to underperform low investment firms (Fama & French, 2015).

The PEAD factor is only weakly correlated with the traditional factors. Its correlation with MKT is -0.135, and with SMB it is -0.084. The largest correlation in absolute value is with MOM, at 0.233, consistent with the idea that earnings announcement surprises contribute to medium–term momentum (e.g., Chan, Jegadeesh & Lakonishok, 1996). Importantly, the correlation between FIN and PEAD is just 0.126, indicating that the two behavioral factors capture largely distinct dimensions of mispricing.

The remaining correlations follow well-known patterns in the factor literature. HML and RMW are strongly negatively correlated ($\rho = -0.785$), as value firms tend to be less profitable, and HML and MOM are negatively related ($\rho = -0.490$), reflecting the tendency for value stocks to lag growth stocks in momentum cycles.

To assess the investment opportunity set offered by different factor models, we next compute the tangency portfolio implied by each model and its corresponding Sharpe ratio. Specifically, for each factor set we estimate the mean vector and covariance matrix of factor returns and derive the mean–variance efficient portfolio with unit exposure to the pricing kernel, following the standard approach in Kan & Zhou (2007). Table 3 reports the resulting Sharpe ratios.

The traditional Fama–French models provide modest Sharpe ratios. A pure market model has a Sharpe ratio of 0.099. Adding SMB and HML (FF3) increases the Sharpe ratio slightly to 0.118. Extending to the five-factor model (FF5) that includes profitability and investment factors raises the Sharpe ratio more substantially to 0.401, and augmenting FF5 with the momentum factor (FF5+MOM) further improves it to 0.494. These values are qualitatively consistent with the evidence that profitability, investment, and momentum strengthen the performance of factor models (Fama & French, 2015; Jegadeesh & Titman, 1993).

Table 2: Correlation matrix of monthly factor returns

	MKT	FIN	PEAD	SMB	HML	RMW	CMA	MOM
MKT	1.000							
FIN	-0.429	1.000						
PEAD	-0.135	0.126	1.000					
SMB	0.102	-0.408	-0.084	1.000				
HML	0.355	0.064	-0.035	-0.003	1.000			
RMW	-0.286	0.098	0.071	-0.074	-0.785	1.000		
CMA	-0.250	0.408	0.065	-0.235	0.508	-0.405	1.000	
MOM	-0.461	0.178	0.233	-0.021	-0.490	0.372	0.046	1.000

Notes: This table reports Pearson correlations between monthly factor returns over the period 2004:01–2023:12. Factors are defined as in Table 1.

Table 3: Sharpe ratios of optimal tangency portfolios by model

Model	Sharpe ratio
MKT	0.099
FF3	0.118
FF5	0.401
FF6	0.494
DHS	0.734

Notes: This table reports the Sharpe ratios of the mean–variance efficient tangency portfolios spanned by each factor set, based on monthly returns from 2004:01 to 2023:12. MKT is the market excess return. FF3 includes MKT, SMB, and HML. FF5 adds RMW and CMA. FF6 augments FF5 with the momentum factor MOM. DHS is the behavioral three-factor model comprising MKT, FIN, and PEAD.

By comparison, the behavioral three-factor DHS model (MKT, FIN, and PEAD) has a Sharpe ratio of 0.734, which is about 49% higher than that of FF5+MOM and roughly 83% higher than that of FF5. In other words, an investor restricted to trading only MKT, FIN, and PEAD can achieve a substantially more attractive mean–variance trade-off than an investor restricted to the conventional Fama–French factors, even when momentum is included. This aligns with the main conclusion of Daniel et al. (2020) for the US market and suggests that the behavioral factors are at least as important in Europe.

Additional tangency portfolios will be obtained including an extended set of factors provided by the literature.

2.4 Spanning tests for behavioral factors

To formally assess whether the behavioral factors FIN and PEAD are spanned by traditional factors, we run time–series spanning regressions of the form:

$$FIN_t = \alpha + \beta' \mathbf{f}_t + \varepsilon_t \tag{7}$$

$$PEAD_t = \alpha + \beta' \mathbf{f}_t + \varepsilon_t \tag{8}$$

where $\mathbf{f}_t$ is a vector of traditional factors. If FIN or PEAD are fully spanned by the chosen factor set, the intercept α should be statistically indistinguishable from zero.

Table 4 reports results for FIN when regressed on FF3, FF5, and FF5+MOM. The estimated alpha remains economically large and statistically highly significant across all specifications. When FIN is regressed on FF3, the alpha is 0.5636% per month with a t–statistic of 6.49 and an R^2 of 0.3645. Adding profitability and investment (FF5) reduces the alpha somewhat to 0.4224% ($t = 5.13$) and increases R^2 to 0.4194. The most demanding specification, FF5+MOM, yields an alpha of 0.3976% per month with a t–statistic of 4.34 and an R^2 of 0.4221 (adjusted $R^2 = 0.4072$). An unexplained return of roughly 0.4% per month (about 5 per year) is both statistically and economically significant, indicating that FIN is far from being spanned by the standard factors.

Table 5 presents analogous spanning tests for PEAD. The evidence here is even more extreme. When PEAD is regressed on FF3, the alpha is 1.0182% per month, with a t–statistic of 10.44 and an R^2 of only 0.0234. Adding RMW and CMA (FF5) reduces the alpha marginally to 0.9814% ($t = 9.88$) and barely increases R^2 to 0.0273. The most comprehensive specification, FF5+MOM, still leaves an alpha of 0.8834% per month with a t–statistic of 8.76 and an R^2 of just 0.0765 (adjusted $R^2 = 0.0527$). Thus, less than 8% of the variance of PEAD is explained by the traditional factors, and the unexplained component carries an annualized premium of roughly 11%.

To better understand how FIN and PEAD load on the traditional factors, Table 6 reports the slope coefficients from the most comprehensive specifications, where each behavioral factor is regressed on FF5+MOM. FIN loads significantly negatively on MKT (-0.1159, $t = -5.21$) and SMB (-0.2851, $t = -4.38$), and positively on HML (0.2501, $t = 3.49$) and RMW (0.3511, $t = 4.60$). This pattern suggests that the FIN factor is long in large, profitable value firms and short in small growth issuers, which is consistent with the interpretation of FIN as capturing long-horizon mispricing related to financing activity. CMA enters with a positive but not statistically significant coefficient (0.1918, $t = 1.65$), while MOM is not significant.

Table 4: Spanning tests: FIN as dependent variable

Model	Alpha (%)	t(Alpha)	R^2	Adj. R^2
FF3	0.5636	6.49	0.3645	0.3564
FF5	0.4224	5.13	0.4194	0.4070
FF6	0.3976	4.34	0.4221	0.4072

Notes: This table reports time–series regressions of FIN on different sets of traditional factors. FF3 includes MKT, SMB, and HML; FF5 adds RMW and CMA; FF6 augments FF5 with momentum factor. Alpha is the monthly intercept in percent. t(Alpha) is the Newey–West t–statistic for testing $\alpha = 0$. R^2 and adjusted R^2 measure the fraction of variation in FIN explained by the traditional factors.

Table 5: Spanning tests: PEAD as dependent variable

Model	Alpha (%)	t(Alpha)	R^2	Adj. R^2
FF3	1.0182	10.44	0.0234	0.0109
FF5	0.9814	9.88	0.0273	0.0065
FF6	0.8834	8.76	0.0765	0.0527

Notes: This table reports time–series regressions of PEAD on FF3, FF5, and FF6, as defined in Table 4. Alpha is the monthly intercept in percent. t(Alpha) is the Newey–West t–statistic for testing $\alpha = 0$. R^2 and adjusted R^2 measure the fraction of variation in PEAD explained by traditional factors.

Table 6: Coefficients: FIN and PEAD regressed on FF5+MOM

	FIN		PEAD	
Factor	Coefficient	t–stat	Coefficient	t–stat
MKT	-0.1159***	(-5.21)	-0.0196	(-0.60)
SMB	-0.2851***	(-4.38)	-0.0670	(-1.19)
HML	0.2501***	(3.49)	0.1637**	(2.26)
RMW	0.3511***	(4.60)	0.1508	(1.38)
CMA	0.1918	(1.65)	-0.1298	(-1.46)
MOM	0.0301	(0.85)	0.1077***	(4.59)
Alpha	0.3976***	(4.34)	0.8834***	(8.76)
Adj. R^2	0.4072		0.0527	

Notes: This table reports time-series regressions of FIN and PEAD on the FF5+MOM factor set: MKT, SMB, HML, RMW, CMA, and MOM. Coefficients are monthly factor loadings. t-statistics (in parentheses) are Newey–West. The row "Alpha" gives the intercept (in percent per month). Adj. R^2 is the adjusted coefficient of determination. ***, **, * denote statistical significance at the 0.01%, 1%, and 5% levels, respectively.

For PEAD, the exposures are generally smaller. The coefficients on HML (0.1637, t = 2.26) and MOM (0.1077, t = 4.59) are statistically significant, which is again intuitive: firms with positive earnings surprises often have characteristics associated with growth and momentum. However, the modest magnitudes of these loadings, combined with the very low R^2, confirm that PEAD is largely orthogonal to the existing factor space. Importantly, in both regressions the alphas remain large and highly significant even after controlling for these exposures.

Taken together, the spanning tests show that both behavioral factors carry substantial incremental information relative to standard models: FIN and especially PEAD earn large and significant alphas when regressed on FF3, FF5, or FF5+MOM, and the variation in these factors is weakly captured for PEAD and only partially for FIN. In combination with the superior Sharpe ratio of the DHS model, this evidence strongly supports the view that the behavioral factors proposed by Daniel et al (2020) are also powerful in explaining the cross–section of European equity returns.

Further spanning tests for behavioral factors will be obtained through an extended set of factors provided by the literature.

2.5 Cross-Sectional Tests: Fama–MacBeth Regressions

Our next set of tests evaluates the explanatory power and risk premia associated with the FIN and PEAD factors within the European equity market. We use portfolios classified according to firm characteristics and factor exposures, and we evaluate pricing performance using both time-series regressions and Fama–MacBeth cross-sectional regressions on portfolio returns. This portfolio-based FMB design allows us to study how FIN and PEAD are priced in the cross-section of European returns. Daniel et al. (2020) perform their main FMB tests at the individual-stock level. We follow the standard approach of the Fama–French and related literature (e.g., Fama & French, 1993; Fama & French, 2015; Hou et al., 2015) by working with portfolios. This choice is motivated by several advantages that are particularly relevant for our European setting. Portfolios reduce idiosyncratic noise and microstructure-related frictions, yielding cleaner measures of systematic risk and more precise estimates of factor loadings and alphas in time-series regressions (e.g., Black et al., 1972; Fama & French, 1993). Sorting stocks into portfolios based on characteristics or factor betas also increases the cross-sectional dispersion in expected returns, which enhances the power of FMB tests to detect non-zero prices of risk for FIN and PEAD conditional on standard factors and controls (e.g., Gibbons et al., 1989; Cochrane, 2005). In addition, portfolio-level betas are more stable and less affected by measurement error than stock-level betas—a particularly important consideration for non-standard factors estimated over relatively short windows—thereby mitigating attenuation bias in the cross-sectional step and improving the interpretability of estimated risk premia (Fama & MacBeth, 1973; Shanken, 1992; Lewellen et al., 2010).

These methodological benefits are especially important in a multi-country European context. Compared to the U.S. market studied by Daniel et al. (2020), European equity markets are more fragmented, with greater heterogeneity in liquidity, trading frictions, and data quality across countries and firm sizes. Portfolio returns help to smooth out these differences and produce return series that more closely resemble the prices of well-defined traded assets in an integrated European setting. In this sense, our portfolio-based FMB framework is both consistent with the main empirical approach to asset pricing and well adapted to the institutional features of European markets.

2.5.1 Firm-level characteristics

To ensure a demanding test of the model, we use 50 value-weighted portfolios as test assets: 25 portfolios sorted by Size and Book-to-Market, and 25 portfolios sorted by Size and Momentum.[4] This expanded set of test assets follows the recommendation of Lewellen et al. (2010) to avoid the high-correlation pitfalls of using Size-BM portfolios alone and to ensure the model can explain multiple dimensions of the cross-section. These 25 size-value and 25 size–momentum portfolios provide a familiar laboratory to assess whether FIN and PEAD improve the pricing of the Fama-French and momentum patterns in European equity returns, and they anchor our analysis in the same portfolio universe that underlies the widely used European Fama-French factors.

Table 7 presents the estimated risk premia (λ) for three specifications—(1) the behavioral model of Daniel et al. (2020), (2) the Fama–French six-factor model (FF6), and (3) a full model integrating both sets of factors—reported separately for Size–Book-to-Market portfolios (Panel A) and Size–Momentum portfolios (Panel B). Across both panels, the results provide clear evidence that the PEAD factor is priced in European markets. In the behavioral specification (Model 1), PEAD earns a monthly premium of 1.18% ($t = 2.64$) in the Size–BM cross-section and 1.90% ($t = 4.80$) in the Size–Momentum cross-section. Importantly, this premium remains economically large and statistically significant in the full model (Model 3), with estimates of 1.15% ($t = 3.41$) and 1.58% ($t = 4.55$), respectively. The robustness of PEAD to the inclusion of the classic Momentum factor (MOM) is particularly noteworthy. While price momentum and earnings momentum are related conceptually, our results show that in Europe they capture distinct dimensions of return predictability. This is consistent with Novy-Marx (2015), who argues that earnings surprises reflect a fundamental underreaction component that price-based momentum cannot fully subsume.

[4] These portfolios were obtained for Europe from Kenneth French's data library and converted from USD to EUR following the currency-conversion procedure of Glück et al. (2021).

Table 7: Fama–MacBeth risk premia by portfolio type

Panel A: 25 Size–Book-to-Market portfolios (5×5)

	Model 1: DHS		Model 2: FF6		Model 3: Full Model	
Factor	λ (%)	t-stat	λ (%)	t-stat	λ (%)	t-stat
Intercept	0.55	(1.91)	0.32	(0.85)	-0.05	(-0.14)
MKT	0.40	(0.68)	0.17	(0.29)	1.65*	(2.44)
SMB			0.07	(0.54)	0.11	(0.83)
HML			-0.03	(-0.14)	-0.03	(-0.14)
RMW			0.49**	(2.63)	0.41*	(2.18)
CMA			-0.15	(-0.70)	-0.07	(-0.34)
MOM			-0.43	(-0.94)	-0.59	(-1.05)
FIN	-0.16	(-0.76)			0.76*	(1.98)
PEAD	1.18**	(2.64)			1.15**	(3.41)
Avg. R^2	0.404		0.629		0.682	

Panel B: 25 Size–Momentum portfolios (5×5)

	Model 1: DHS		Model 2: FF6		Model 3: Full Model	
Intercept	0.42	(1.69)	0.92**	(3.28)	0.70**	(2.70)
MKT	0.59	(1.31)	-0.06	(-0.12)	0.82	(1.47)
SMB			0.18	(1.50)	0.22	(1.87)
HML			-1.03*	(-2.38)	-1.01*	(-2.39)
RMW			0.80**	(2.83)	0.43	(1.65)
CMA			0.68**	(3.30)	0.60**	(2.84)
MOM			0.65**	(2.62)	0.60*	(2.42)
FIN	-0.49	(-1.84)			-0.12	(-0.41)
PEAD	1.90***	(4.80)			1.58***	(4.55)
Avg. R^2	0.515		0.647		0.709	

Notes: This table reports average cross-sectional risk premia (λ) from Fama–MacBeth regressions run for the 25 Size–Book-to-Market portfolios (Panel A) and the 25 Size–Momentum portfolios (Panel B). Betas are estimated from time-series regressions using each factor set and then used in monthly cross-sectional regressions. t-statistics (in parentheses) are computed using Newey–West standard errors. ***, **, * denote statistical significance at the 0.01%, 1%, and 5% levels, respectively. The sample period is January 2004 to December 2023, and all returns are denominated in EUR.

The pricing of FIN is more nuanced and appears to depend on the set of test assets. In Panel A (Size–BM), FIN is insignificant in the behavioral model (Model 1) but becomes positive and marginally significant in the full specification (0.76%, $t = 1.98$). This sign reversal suggests that FIN shares nontrivial common variation with traditional factors (especially value and profitability-related exposures): in the parsimonious behavioral specification part of FIN's cross-sectional signal is absorbed by omitted classic factor components, whereas in the full model FIN is effectively identified off its incremental component orthogonal to FF6. In the same vein, FIN may be priced primarily along the value dimension emphasized by the Size–BM test assets, consistent with financing activity being more informative for misvaluation among firms where valuation and profitability characteristics are most salient. In contrast, Panel B shows a negative FIN premium in Model 1 (-0.49%, $t = -1.84$) that becomes economically small and insignificant once FF6 factors are included (-0.12%, $t = -0.41$). Taken together, these estimates suggest that the cross-sectional price of FIN is not stable across portfolio sorts, and may be sensitive to the characteristics emphasized by the test assets. This cross-sectional instability is consistent with the view that FIN captures mispricing related to corporate financing activity whose compensation may be state-dependent or concentrated in specific regions of the cross-section, even if FIN remains highly significant in the time-series spanning tests (Baker & Wurgler, 2006; Stambaugh & Yuan, 2015, 2017).

Regarding the benchmark models, Panel A indicates that the FF6 model prices profitability and momentum-related variation through a significant RMW premium (0.49%, $t = 2.63$), whereas Panel B shows broader pricing of traditional factors, with significant premia for HML (-1.03%, $t = -2.38$), RMW (0.80%, $t = 2.83$), CMA (0.68%, $t = 3.30$), and MOM (0.65%, $t = 2.62$). Once the behavioral factors are added (Model 3), PEAD remains the dominant and most robust premium in both panels, while some traditional premia attenuate (e.g., RMW in Panel B and CMA remains significant). Consistent with this, the average cross-sectional R^2 increases when moving from FF6 to the full model in both panels—from 62.9% to 68.2% in Panel A and from 64.7% to 70.9% in Panel B—confirming that the behavioral framework adds incremental explanatory power beyond traditional production- and characteristic-based models (Fama & French, 2015; Hou et al., 2015).

2.5.2 Beta-sorted portfolios

In the Fama–French tradition, portfolios such as size–book-to-market are constructed directly from firm-level characteristics, because these variables represent relatively stable and economically meaningful primitives that predate any particular factor model. Market capitalization and book-to-market ratios are fundamental attributes of firms, and decades of empirical evidence show that these characteristics predict average returns in a way that is not tied to any single factor specification (e.g., Fama & French, 1992; Fama & French, 1993). Consequently, the corresponding factors—SMB and HML—are derived from these characteristics, not the other way around. By contrast, the DHS behavioral mispricing factors (FIN and PEAD) occupy a different position relative to their firm-level inputs. These factors originate from signals such as net issuance activity for FIN or earnings-related abnormal returns for PEAD, but the underlying firm-level signals are noisy, heterogeneous, and only imperfectly aligned with the common behavioral mechanisms of interest. Daniel et al. (2020) emphasize that it is the factor-mimicking portfolios—the FIN and PEAD factor returns—that isolate the economically relevant common component of mispricing, rather than any particular accounting or market-based variable. In this sense, a stock's exposure to FIN or PEAD, i.e. its factor beta, can provide a more parsimonious and robust summary of its relation to the underlying behavioral process than the raw signal used to construct the factor. This logic is closer in spirit to the beta-sorted portfolio constructions used in models where the factor itself is the primitive object, such as the liquidity-risk factor of Pástor & Stambaugh (2003), the betting-against-beta factor of Frazzini & Pedersen (2014), or the tail-risk factor of Kelly & Jiang (2014). In those settings—and analogously for FIN and PEAD—sorting on factor betas, rather than on heterogeneous firm-level signals, is the natural way to form test assets that span the economically relevant dimension of risk or mispricing.

Against this background, each month, we estimate factor loadings for individual stocks using rolling-window time-series regressions of excess returns on the market factor, and the FIN and PEAD factors. Based on these ex ante betas, we form 5×5 size–beta(FIN) portfolios by first sorting stocks into five size quintiles and, within each size quintile, into five quintiles according to their estimated FIN beta, yielding 25 size–beta(FIN) portfolios. Analogously, we sort stocks into 5×5 size–beta(PEAD) portfolios using the estimated PEAD beta, obtaining 25 size–beta(PEAD) portfolios. These beta-sorted portfolios are designed to capture variation in expected returns associated with differential exposure to FIN and PEAD across the size distribution, and they constitute our primary behavioral test assets.

We further summarize the pricing of FIN and PEAD through simple long–short factor-mimicking portfolios. For each relevant sorting scheme, we construct High–Low portfolios that go long the highest-beta quintile and short the lowest-beta quintile, either within size buckets or at the aggregate level. These High–Low portfolios provide a parsimonious representation of the FIN and PEAD premia and are used both as standalone test assets and, when appropriate, as additional factors in our time-series regressions.

Finally, to study the interaction between traditional characteristics and behavioral exposures, we construct two additional sets of 5×5 portfolios. First, we form value–beta(FIN) portfolios by sorting stocks each month into five book-to-market quintiles and, within each quintile, into five quintiles based on their estimated FIN beta, yielding 25 value–beta(FIN) portfolios. Second, we construct momentum–beta(PEAD) portfolios by sorting stocks into five momentum quintiles and, within each, into five quintiles based on the estimated PEAD beta, producing 25 momentum–beta(PEAD) portfolios. These interaction portfolios allow us to assess whether FIN is priced conditional on value and whether PEAD captures variation in expected returns beyond standard momentum.[5]

[5] At present, the cross-sectional tests using beta-sorted portfolios are still uncompleted. Further versions of our research will enhance the validation of the DHS model in Europe with an extended set of competing factors in line with the approach of Daniel et al. (2020). This work is still in progress, but details in advance are available upon request.

3 Application of the DHS model to the European equity fund industry

European mutual fund industry reached €23.4 trillion in net assets at the end of 2024, of which €15.3 trillion were UCITS (Undertakings for Collective Investment in Transferable Securities), gaining €630 billion of net inflows into these collective portfolios. At the end of 2024, there are 67,940 European-domiciled funds with an average fund size of €345 million, which it notes is materially higher than a decade earlier. This large universe of funds spans a wide range of management strategies but operating under a common UCITS rulebook, creating a rich setting for studying competition, scale effects, and product design within a regulated fund framework.

In terms of composition, European mutual funds are concentrated in traditional, liquid asset classes, which helps to explain their importance in both investor portfolios and policy discussions. At the end of 2024, equity mutual funds represented 33% of net assets and bond mutual funds 20%, followed by multi-asset funds (18%), money market funds (9%), and other investment categories, including real estate, (20%). These figures highlight equity funds at the center of how European fund assets are allocated across major public financial markets.[6]

Recent structural trends in the European fund industry report an increasing concentration by size, sustained shift toward passive investing, and a fee pressure, with average ongoing charges declining between 2020 and 2024 for both active and passive funds. This evolving landscape suggests that the European equity fund industry is a compelling laboratory to examine whether its returns reflect stock-picking skills, systematic exposures, or compensated (or uncompensated) trading in mispricing. For mutual funds, this distinction is relevant because managers may appear to generate alpha when they are, in fact, loading on return-driving characteristics intentionally or unintentionally through portfolio construction (Kacperczyk et al., 2005; Barber et al., 2016; Berk & van Binsbergen, 2015). This question motivates the use of the DHS model, which is explicitly designed to capture behavioral mispricing dynamics at different horizons. Applying a behavioral factor structure that targets behavioral mispricing directly complements the existing research on standard factors.

The European equity fund settings also sharpen the economic content of the DHS model because the ability to exploit behavioral mispricing is plausibly conditioned by the same constraints found in the mutual fund literature. There is robust evidence supporting that managers' ability to exploit mispricing is affected by multiple factors. Genuine skills may be hidden by costs, constrained by institutional mandates, and inadequately rewarded by flows responding to heuristics. Regulatory requirements, style classifications, ESG policies, market

[6] The European industry statistics included in this section are reported by EFAMA (2025).

frictions, and career concerns limit these management skills. Pástor & Stambaugh (2002) find that mutual funds may appear to underperform due to liquidity risk exposure rather than lack of skills. Cremers et al. (2013) argue that capitalization-weighted benchmarks are suboptimal, forcing managers to choose between exploiting mispricing and managing career risk. Amihud & Goyenko (2013) show that low R-squared funds outperform but exhibit higher volatility, dissuading risk-averse investors. Market frictions, including liquidity constraints and transaction costs, further limit managers' ability to exploit mispricing. At the same time, investors' capital allocation may not reward these return drivers. Barber et al. (2016) find that investors respond to past returns and Morningstar ratings but show limited sensitivity to factor exposures. Evans & Sun (2021) also demonstrate that retail investors rely on heuristics and star ratings rather than sophisticated performance measures based on asset pricing models. The growing attention to sustainability adds another relevant constraint to this management framework. Hartzmark & Sussman (2019) provide evidence that sustainability ratings drive fund flows independent of performance, potentially restricting managers' investing universe and excluding profitable opportunities in low-ESG firms.

The application of the DHS model to a comprehensive sample of European equity funds will assess whether European equity fund returns are driven by systematic exposures to short- and long-horizon behavioral mispricing, and identify the economic contribution of the exposure to these behavioral factors in the returns. This section helps to connect asset-pricing evidence on behavioral factors to questions of industry performance in one of the world's most important regulated fund markets.

3.1 Mutual fund sample

Our primary data source is Morningstar, from which we retrieve comprehensive information on European equity mutual funds with an investment focus on the Euroland. We initially collect data on equity funds with legal structures classified as open-end funds, fonds communs de placement (FCP), and unit trusts. The raw dataset contains 1,895 survivorship-bias-free share classes launched up to December 2023.

To ensure consistency and to avoid multiple counting of the same underlying investment vehicle, we aggregate the share-class information at the fund level. Following standard practice in the mutual fund literature, we retain only those funds with at least 36 consecutive monthly observations of gross returns available during the sample period. The return data span from January 2014 to December 2023, providing a sufficiently long time series for robust estimation in our asset pricing tests.

Table 8: Summary statistics of fund sample

Panel A: Statistics at fund-month level

Variable	N	Mean	SD	P25	Median	P75
Net Return (%)	40,632	0.492	4.601	-2.199	0.712	3.238
Fund Age (Years)	41,484	15.313	11.194	8.463	14.775	20.353
Expense Ratio (%)	6,928	1.476	0.877	0.970	1.510	1.800
Flow (%)	39,640	1.429	139.589	-1.043	-0.111	0.511
Fund Size (€M)	41,150	167.469	300.104	20.227	59.599	178.835
Morningstar Rating	33,393	2.927	1.069	2.000	3.000	4.000

Panel B: Statistics at fund level

Variable	N	Mean	SD	P25	Median	P75
Net Return (%)	405	0.480	0.259	0.375	0.506	0.616
Fund Age (Years)	405	14.398	11.033	6.911	13.448	19.418
Expense Ratio (%)	119	1.540	0.767	1.006	1.590	1.896
Flow (%)	387	2.789	31.225	-0.677	-0.001	0.893
Fund Size (€M)	405	150.745	265.674	19.605	58.182	161.056
Morningstar Rating	380	2.894	0.895	2.213	2.909	3.469
Months per Fund		102.430	26.034	88	120	120

Notes: This table reports summary statistics for our sample of 405 Euroland equity funds from January 2014 to December 2023. The sample is restricted to funds with at least 36 consecutive monthly return observations. Panel A presents statistics at the fund-month level. Panel B reports cross-sectional statistics, where each variable is first averaged at the fund level over its available history. Net Return is the monthly net-of-fees return, expressed in percent. Fund Age is the number of years since the inception of the fund's oldest share class. Expense Ratio is the annual net expense ratio, expressed in percent. Flow is the monthly percentage change in fund assets unrelated to fund performance. Fund Size is the total net assets under management, expressed in millions of euros. Morningstar Rating represents the fund's "Star Rating," a quantitative, risk-adjusted measure of a fund's past performance relative to its Morningstar Category peers, ranging from one to five stars. Months per Fund indicates the time-series length of the fund observations. For each variable, we report the number of observations (N), the mean, standard deviation (SD), and the 25th, 50th (median), and 75th percentiles.

We further restrict the sample to funds whose base currency is the euro, thereby eliminating potential distortions arising from currency fluctuations and ensuring comparability across portfolios operating within the Euroland. Table 8 provides a comprehensive summary of the fund sample characteristics. Panel A presents the pooled fund-month observations, while Panel B reports the cross-sectional distribution of fund-level averages. The final sample consists of 405 funds with an average time-series history of 102 months, indicating that the majority of funds in our sample are present for nearly the entire ten-year period.

The average fund in our sample is well-established, with a cross-sectional mean age of 14.4 years (Panel B). In terms of size, the sample exhibits significant heterogeneity; while the average fund manages €150.7 million, the median size of €58.2 million reveals a distribution where a relatively small number of large funds account for a significant portion of the total assets under management. The average net expense ratio stands at 1.54%, which is consistent with the cost of active management in the European equity market reported by ESMA (2025b).

The funds report an average monthly net return of 0.48% (Panel B), with a cross-sectional standard deviation of 0.26%. This suggests that while the average fund generates positive returns during our sample period, there is meaningful dispersion in performance across managers. The Morningstar Rating further corroborates this, with a cross-sectional mean of 2.89 stars, aligning with the expected distribution of risk-adjusted performance. Finally, the Flow variable shows a median near zero (-0.001%), although the high mean (2.79%) and standard deviation (31.2%) in the cross-section suggest that aggregate capital growth is driven by strong inflows into a subset of funds.

3.2 Long-run exposure to factors

We begin by estimating each fund's average exposure to mispricing factors using time-series regressions over the full available sample. This step aims to characterize funds' long-run exposure profiles and to assess whether funds systematically load on mispricing-related strategies once standard risk factors are taken into account. We consider a specification in which the factor set includes the DHS mispricing factors (FIN and PEAD), as well as standard Fama–French factors, momentum, and a set of standard control variables used in the mutual fund literature including size, flows, and age.[7] The estimated beta coefficients are interpreted as measures of average long-run exposure to each factor.

Figure 1 reveals that strong heterogeneity in factor exposures across European equity funds. Market betas are almost universally significant (99% of funds at $p<5\%$ level), indicating that funds operate with substantial and persistent market exposure, in line with the broad evidence in the performance-evaluation literature. Standard style factor exposures display a more nuanced pattern: SMB exhibits the strongest and most systematic negative exposure among style factors (51% of funds at $p<5\%$ level), whereas HML, RMW, MOM, and especially CMA, show considerably weaker and less consistent loadings, both positive and negative. The behavior of the DHS factors is particularly informative. FIN shows a remarkably strong pattern: 82% of funds have a statistically significant loading at $p<5\%$ level, and these loadings are predominantly negative, suggesting that European managers systematically tilt toward firms with high net issuance. In contrast, PEAD displays almost

[7] Expense ratio is excluded from our set of control variables due to the scarce availability of this information in our fund sample (see Table 8). However, the empirical results obtained for the subset of funds including this control variable are consistently similar to the findings provided in this section. Detailed results are available upon request.

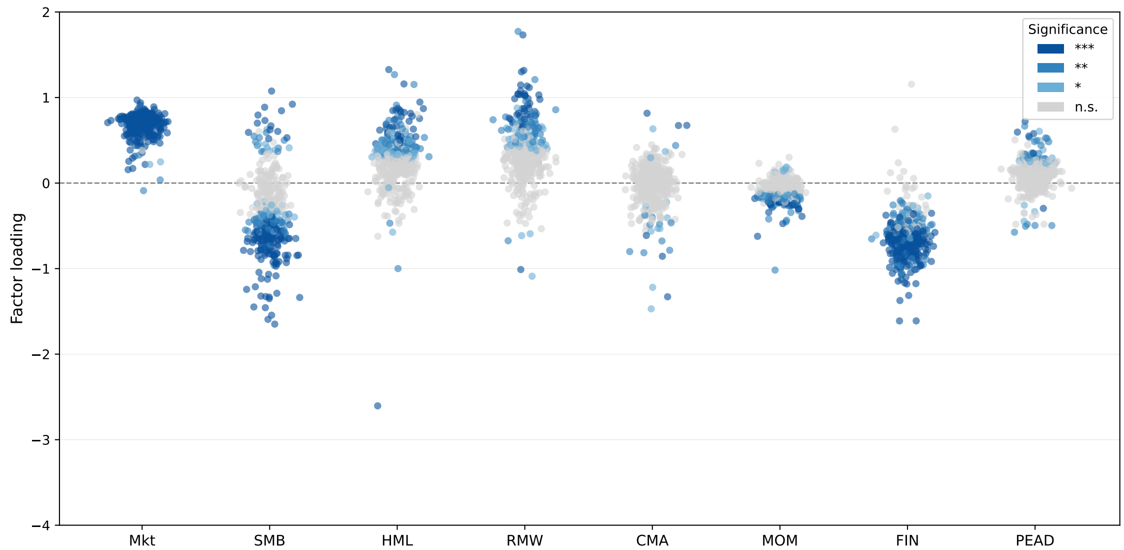

Figure 1: Distribution of factor loadings and statistical significance across European equity funds. Each point represents the estimated beta of a fund with respect to one of the seven factors. Colors denote statistical significance: dark blue (***) for $p < 0.01$, medium blue (**) for $p < 0.05$, light blue (*) for $p < 0.10$, and gray for non-significant loadings. The dashed line marks zero.

no explanatory power, with 88% of funds exhibiting statistically insignificant loadings. Overall, the evidence highlights the central role of FIN in capturing systematic exposures among European funds—stronger than several standard Fama–French factors—while PEAD appears largely irrelevant in this setting. While long-term behavioral mispricing plays a significant role in the systematic exposures of the European equity funds, short-term behavioral mispricing caused by limited investor attention to earnings-related events does not concern European fund managers. This negative and significant exposure to FIN factor in the European equity fund industry suggests that managers search for slow-moving price corrections related to long-term behavioral mispricing.

3.3 Performance analysis

The performance evaluation results in Table 9 confirm that European equity funds exhibit a systematic and significant negative exposure to the long-horizon financing factor (FIN), which remains robust even after controlling for the Fama-French six-factor model and fund-level characteristics. In contrast, the exposure to the short-horizon PEAD factor is not statistically different from zero across all specifications, highlighting the previous result that mutual fund managers do not or cannot exploit earnings-related underreaction due to the high turnover and trading frictions associated with such event-driven strategies. Notably, the inclusion of behavioral factors in the full model (DHS+FF6) improves the explanatory power (R-squared of 0.725) and yields a positive, though non-significant, alpha, suggesting that what traditional models might classify as unexplained performance is, in part, a compensation for systematic factor allocations. This finding is consistent with the idea that, conditional on the standard FF6 factors, financing-related effects may capture an additional dimension of systematic return variation, and that introducing FIN can reallocate explanatory power across these factors. The resulting change in alpha from slightly negative under FF6 model to slightly positive under DHS+FF6 model should therefore be interpreted mainly as a change in attribution and benchmark specification rather than as a robust increase in statistically significant abnormal performance.

Table 9: Performance evaluation

	DHS		FF3		FF6		DHS+FF6	
Factor	Coeffic.	*t*-stat	Coeffic.	*t*-stat	Coeffic.	*t*-stat	Coeffic.	*t*-stat
Alpha	-0.174	(-0.547)	-0.049	(-0.175)	-0.046	(-0.158)	0.089	(0.292)
MKT	0.781***	(14.874)	0.813***	(20.706)	0.770***	(17.666)	0.697***	(14.97)
FIN	-0.245*	(-1.958)					-0.628***	(-4.154)
PEAD	0.104	(0.845)					0.086	(0.776)
SMB			-0.136	(-1.092)	-0.14	(-1.072)	-0.335**	(-2.566)
HML			0.032	(0.437)	0.156	(0.981)	0.278*	(1.925)
RMW					0.22	(1.091)	0.384*	(1.921)
CMA					-0.147	(-0.752)	-0.001	(-0.003)
MOM					-0.068	(-1.126)	-0.096	(-1.552)
Size	0.030**	(2.271)	0.024*	(1.825)	0.024*	(1.793)	0.026**	(1.992)
Age	-0.033	(-1.090)	-0.05	(-1.474)	-0.051	(-1.487)	-0.027	(-0.959)
Flows	0.000***	(2.939)	0.000***	(3.023)	0.000***	(2.708)	0.000***	(3.604)
N	38668		38668		38668		38668	
R^2	0.701		0.697		0.701		0.725	
Adj.R^2	0.701		0.697		0.701		0.725	

Notes: This table reports the coefficient estimates from panel regression of monthly fund excess returns on multi-factor asset pricing models from 2014:01 to 2023:12. DHS is the behavioral three-factor model of Daniel et al (2020) comprising MKT, FIN, and PEAD. FF3 includes MKT, SMB, and HML. FF6 extends FF3 by adding RMW, CMA, and MOM factors. DHS+FF6 combines the behavioral factors with the six-factor model. MKT is the market excess return. All models include fund-level control variables: the natural logarithm of the assets under management (Size), the logarithm of fund age in years (Age), and monthly fund flows expressed as a percentage of lagged assets (Flow). t-statistics, based on standard errors two-way clustered by fund and month, are reported in parentheses..***, **, * denote statistical significance at the 0.01%, 1%, and 5% levels, respectively.

3.4 Cross-sectional pricing and economic attribution

In the second step, we assess whether exposures to behavioral factors are priced in the cross-section of funds and quantify their economic relevance using the Fama–MacBeth two-pass regression methodology. This approach allows us to separate the estimation of factor exposures from the estimation of factor prices and to conduct inference that is robust to cross-sectional dependence.

We first estimate time-varying factor loadings for each fund using 36-month rolling-window time-series regressions. For each fund i and month t, factor loadings $\widehat{\beta}_{i,t-1}$ are obtained using information available up to month $t-1$. These loadings proxy for the ex-ante exposure relevant for pricing and mitigate concerns related to look-ahead bias.

In each month t, we then estimate the following cross-sectional regression:

$$r_{i,t} = \lambda_{0,t} + \lambda_t' \, \widehat{\beta}_{i,t-1} + \gamma_t' \, Z_{i,t-1} + u_{i,t} \tag{9}$$

where λ_t' denotes the vector of cross-sectional factor prices. In all specifications, the cross-sectional regressions include the Fama–French factors and momentum, so that the estimated prices for FIN and PEAD capture their marginal contribution to explaining the cross-section of fund returns conditional on standard risk factors. Average factor prices are computed as time-series averages of the monthly cross-sectional estimates, with statistical inference based on heteroskedasticity- and autocorrelation-consistent (Newey–West) standard errors. Z reflects the vector of standard control variables used in the mutual fund literature, including log(size), log(age), and flows in percentage.

Table 10 reports the average Fama–MacBeth prices of risk and Newey–West t–statistics for the set of factors. Both FIN and PEAD factors exhibit negative and statistically insignificant prices. Daniel et al. (2020) constructs the FIN factor as a portfolio that is long in firms with low net equity issuance and short in firms with high net issuance. Intensive equity issuers tend to be overvalued and earn relatively low subsequent returns, whereas low–issuance firms tend to be undervalued and earn higher future returns. A positive loading on FIN therefore represents an exposure that is long in undervalued low–issuance firms and short in overvalued issuers, while a negative loading corresponds to the opposite configuration. In our European mutual fund sample, the vast majority of funds show negative and often statistically significant FIN betas, indicating that they are systematically tilted toward net equity issuers. This pattern is consistent with benchmarked, largecap or growth–oriented mandates that overweight firms more likely to tap equity markets.

Table 10: Fama–MacBeth factor risk premia

Factor	$\hat{\lambda}$	SE (NW)	t-stat	p-value
Intercept	0.181	0.162	1.120	0.267
MKT	0.370	0.421	0.880	0.381
FIN	-0.096	0.124	-0.778	0.439
PEAD	-0.068	0.109	-0.624	0.535
SMB	-0.022	0.162	-0.136	0.892
HML	-0.083	0.286	-0.290	0.773
RMW	0.012	0.152	0.077	0.939
CMA	-0.157	0.187	-0.841	0.403
MOM	-0.097	0.239	-0.406	0.686

Notes: The table reports average factor risk premia estimated using the two-step Fama–MacBeth procedure. Standard errors are corrected using the Newey–West estimator.

Given this cross–sectional configuration of exposures, the negative estimate of the FIN price of risk in Table 10 is not indicative of a failure of the FIN factor. Rather, it reflects that funds with more negative FIN loadings—that is, those more heavily tilted toward high–issuance firms—earn lower average returns, whereas funds with less negative (or slightly positive) FIN betas perform better. The Fama–MacBeth procedure internalizes this by assigning a negative price of risk to FIN so as to reconcile the monotonic relation between FIN exposure and realized returns when most assets lie on the *wrong* side of the issuance anomaly. Thus, the evidence is consistent with the interpretation that long–horizon mispricing associated with financing activity remains relevant in Europe, but the mutual fund industry is, on average, positioned on the losing side of this factor.

By contrast, the PEAD factor behaves very differently. PEAD is designed to capture short–horizon mispricing related to post–earnings announcement drift, constructed as a portfolio that is long in firms with unusually positive short–term returns around earnings announcements and short in firms with negative drift. In our data, mutual funds exhibit PEAD betas that are small in magnitude, predominantly insignificant, and with no clear directional clustering. This lack of systematic exposure is consistent with the institutional and regulatory context in which European mutual funds operate: the very short horizon of the PEAD anomaly, combined with turnover constraints and trading frictions, makes it unlikely that such funds deliberately exploit, or even unintentionally load on, earnings–announcement–driven drift (consistent with the high Sharpe ratio in Table 1 for this factor).

Consequently, the average PEAD price of risk reported in Table 10 is negative but far from statistically significant. Taken together, our findings align with the central distinction in Daniel et al. (2020): long–horizon mispricing associated with firms' financing decisions (FIN) is a dimension along which institutional portfolios in Europe are meaningfully exposed, whereas short–horizon mispricing linked to earnings announcements (PEAD) is largely orthogonal to their investment choices and does not emerge as a priced source of mispricing.

Finally, we quantify the economic contribution of mispricing exposures by combining estimated factor prices with fund-level exposures. The average contribution of factor k to fund i is defined as:

$$\overline{C}_{i,k} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\beta}_{i,k,t-1}\widehat{\lambda}_{k,t}. \tag{10}$$

This expression can be decomposed into two components:

$$\overline{C}_{i,k} = \bar{\beta}_{i,k}\bar{\lambda}_k + \mathrm{Cov}(\widehat{\beta}_{i,k,t-1},\, \widehat{\lambda}_{k,t}), \tag{11}$$

where the first term *(Level)* captures the contribution associated with maintaining an average exposure to the factor, while the second term *(Timing)* reflects gains or losses associated with changes in exposure across periods with different cross-sectional factor prices.

To assess economic significance, we scale the contributions by assets under management of each fund on an annual basis, and we aggregate them across funds. This allows us to assess the relevance of mispricing factors in monetary terms.

Table 11 reports the economic attribution of FIN and PEAD exposures aggregated across European equity funds and expressed in monetary terms. For FIN, the total contribution is positive and economically sizable. Most of this contribution is driven by the level component, indicating that maintaining an average exposure to FIN is rewarded in the fund cross-section once standard risk factors are controlled for. At the same time, the timing component is also positive and economically meaningful, suggesting that variations in exposure tend to occur in periods in which the cross-sectional price of FIN is relatively more favorable.

The results for PEAD display a markedly different pattern. The level component is negative, implying that a persistent exposure to PEAD is not rewarded on average in the fund sample conditional on Fama–French and momentum factors. However, the timing component is positive and more than offsets the negative level effect, yielding a small but positive total contribution. This result denotes that the economic value associated with PEAD exposures arises mainly from time variation in exposure rather than from a stable average tilt.

Taken together, these findings suggest that mispricing factors differ not only in their cross-sectional prices but also in the channels through which they generate economic value for funds. FIN appears to deliver value largely through a stable exposure channel, complemented by positive timing effects, whereas PEAD contributes positively only through dynamic adjustments in exposure. This contrast highlights the importance of distinguishing between level and timing components when assessing the economic relevance of mispricing-related strategies in a fund setting.

Table 11: Economic attribution of FIN and PEAD exposures

Factor	Component	Aggregate (EUR/year)	Average per fund (EUR/year)
FIN	Total	8,193,349	21,281
FIN	Level	3,424,642	8,895
FIN	Timing	4,768,463	12,385
PEAD	Total	44,153	114
PEAD	Level	-855,942	-2,223
PEAD	Timing	900,107	2,337

Notes: This table reports the annualized economic contribution of FIN and PEAD exposures aggregated across European equity funds. *Total* denotes the average contribution $\frac{1}{T}\sum_t \widehat{\beta}_{i,k,t-1}\widehat{\lambda}_{k,t}$, *Level* corresponds to $\bar{\beta}_{i,k}\bar{\lambda}_k$, while *Timing* is the difference between the total and the level component and is equivalent to $\mathrm{Cov}(\widehat{\beta}_{i,k,t-1}, \widehat{\lambda}_{k,t})$. Cross-sectional prices $\widehat{\lambda}_{k,t}$ are obtained from Fama–MacBeth regressions including the DHS+FF6 and fund control variables. Monetary attribution is obtained by scaling return-based contributions by each fund's average assets under management over the sample period.

The evidence from portfolio-based pricing tests and from the fund-level analysis is complementary. Table 7 reports Fama–MacBeth estimates obtained using characteristic-sorted equity portfolios as test assets and shows that PEAD commands a positive and statistically significant cross-sectional mispricing premium, while FIN does not appear to be priced in that setting. These results validate the relevance of PEAD as a mispricing factor when test assets are designed to isolate the underlying return dimension.

When the same factors are used on mutual funds, however, the interpretation of the estimated prices changes. In the fund universe, cross-sectional prices reflect the marginal compensation for exposures within a setting characterized by long-only constraints, net-of-fee returns, heterogeneous mandates, and conditioning on standard risk factors. Consequently, the average cross-sectional price of PEAD can be negative even though the factor earns a positive average return in portfolio-based tests. Our economic attribution results show that, in this context, PEAD generates value primarily through variations in exposure across periods rather than through a persistent average tilt. By contrast, FIN exhibits a positive economic contribution in the fund cross-section, despite its weak pricing performance in portfolio tests, suggesting that its relevance for funds arises from heterogeneity in exposure and implementation rather than from a stable portfolio-level risk premium.

Overall, these findings highlight that portfolio-based Fama–MacBeth tests assess whether a factor prices well-constructed equity portfolios, whereas fund-based tests capture how the same factor is priced and monetized within the institutional constraints faced by professional investors. The distinction helps reconcile the two sets of results and underscores the importance of using fund-level test assets when the objective is to understand how mispricing-related strategies translate into economic outcomes for investors.

4 Conclusions

This study validates the DHS behavioral pricing model in European equity markets and assesses whether these behavioral mispricing factors matter for European equity funds. Using Europe-specific implementations of the long-horizon financing factor (FIN) and the short-horizon post–earnings announcement drift factor (PEAD), the results show that behavioral mispricing is present in Europe and is economically important for both asset pricing in European equity markets and performance attribution of the European fund industry.

On the asset-pricing side, both behavioral factors earn large and statistically significant premia in Europe over 2004–2023, being short-horizon PEAD particularly strong. Both factors are weakly correlated with each other and are largely orthogonal to standard pricing factors. Spanning tests reinforce this finding. Even after controlling for a complete set of pricing factors, both FIN and PEAD report economically large and significant intercepts, especially PEAD. In mean–variance terms, the parsimonious DHS factor set also spans a better opportunity set than standard benchmarks in our sample.

On the mutual fund side, European equity funds report substantial heterogeneity in behavioral mispricing factor loadings. The long-horizon FIN exposure stands out with significant tilts toward net equity issuers. By contrast, PEAD loadings are mostly small and statistically insignificant, which fits the short-horizon, event-driven nature of PEAD and the practical limitations faced by the highly-regulated European mutual funds, such as trading frictions, mandates, and implementation costs. In fund-level Fama–MacBeth tests, neither FIN nor PEAD emerges as strongly priced on average once standard factors are included. However, the economic attribution evaluation shows that FIN exposure still contributes meaningfully in monetary terms at the industry level, largely through a stable level component complemented by positive timing, whereas PEAD's contribution—when present—comes primarily through time variation rather than persistent average tilts.

Overall, the evidence supports that European equity returns are significantly shaped by behavioral mispricing related to both financing activity and earnings underreaction, expanding the pricing factor space beyond standard pricing models. However, European equity funds do not exploit these opportunities symmetrically. While long-horizon financing-related mispricing significantly contributes to funds' systematic exposures and economic attribution, short-horizon earnings underreaction remains largely outside the mutual fund portfolios.

Future work on this paper should sharpen these conclusions by exploring state-dependent pricing of DHS factors, differences across countries and legal regimes within Europe, and how mutual fund characteristics shape the ability of active managers to exploit systematic exposures to long- and short-horizon behavioral mispricing opportunities.

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