Do Retailers Trade Noise? Macroeconomic Luck and the Mispricing of Stocks

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Abstract

Macroeconomic noise - an impact on corporate performance from temporary macro conditions - potentially introduces significant bias into the forecasts of growth and profits that underlie corporate valuations. We classify companies into portfolios based on whether recent macroeconomic noise has positively or negatively impacted their operating performance. A portfolio strategy that goes long on companies facing macroeconomic headwinds and short on those with tailwinds yields an annualised excess return of 10%. The evidence suggests that the market consistently overvalues companies that have recently benefited from favourable macroeconomic conditions. Further analysis suggests that retail investors are prone to buying into macroeconomic luck, exposing them to subsequent reversals, while sophisticated institutional investors tend to sell before the reversal occurs.

Keywords: *retailers, macroeconomic noise, sustainable profits, efficient market, factor returns*

JEL Codes: G32, G31, L71

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1. Introduction

Two key determinants of stock prices are a company's expected growth rate and profitability. According to the efficient market hypothesis, investors are assumed to process all value-relevant information rationally when forecasting these factors, including insights from recent financial performance. However, such performance can be heavily influenced by macroeconomic noise—favorable or unfavorable conditions arising from economic forces beyond management's control. While traditional macroeconomic indicators such as GDP, productivity growth, and aggregate demand are certainly relevant in this context, they ultimately translate into fluctuations in exchange rates, interest rates, and inflation, which can have a profound impact on a firm's competitiveness and operational performance (Oxelheim & Wihlborg, 2008).[1]

Macroeconomic noise can be thought of as "luck"—random impacts on firms that tend to be short-lived. What makes this noise compelling from an asset pricing perspective is that it is largely indistinguishable from the sustainable profits and growth rates that, according to financial theory, genuinely drive firm value. When a firm releases its financial statements, it is rarely clear how much of its performance is influenced by favourable ("tailwind") or unfavourable ("headwind") macroeconomic factors. Unfortunately, firms often give investors only limited insight into how the macroeconomic environment has shaped their results. For example, Oxelheim (2019) finds that none of the 100 largest public companies in Europe supplied information that would allow the outside shareholders to fully comprehend the development of intrinsic performance.[2]

[1] The academic literature on macroeconomic exposure emphasises that the guiding principle is to find macroeconomic variables that influence the corporate performance and which are easy to measure and more or less instantaneously observable. Oxelheim (2019) states: "Deviations from International Fisher Parity and Purchasing Power Parity generate excess profit and losses. Based on these two relationships, and with the requirement of ease of measurement without any delay, the macroeconomic influences can be measured as channeled through fluctuations in exchange rates, interest rates and inflation."

[2] This is not to say that they do not disclose any information. The disclosure of foreign exchange and interest rate exposures can be quite detailed. However, these tend to be partial and illustrate forward-looking estimates of the sensitivities of some arbitrarily selected performance measure to a change in the home currency. These

We propose that macroeconomic luck leads to temporary misvaluations because investors struggle to separate it from sustainable performance. Essentially, the market values this noise on par with enduring profits, leading investors to project the effects of macroeconomic luck into the future, despite its temporary nature. In cases of tailwind, this results in overvaluation relative to fundamentals, while headwind leads to undervaluation. As the influence of luck fades, the market adjusts, and stock prices revert. If this hypothesis holds, tailwind (headwind) should negatively (positively) predict future returns. A dynamic of this kind was evident during the Covid-19 pandemic, when extraordinary conditions favoured certain tech companies, driving sharp price increases. As markets normalised and unsustainable growth rates diminished, valuations fell accordingly.[3]

In fact, valuation experts, including Koller et al (2020), often emphasise that projecting past high growth into the future is among the most critical valuation errors. A deep strand of the finance literature, starting with De Bondt and Thaler (1985, 1987), supports the idea that investors overreact to recent events and extrapolate fundamentals. Barberis, Shleifer & Vishny (1998) capture the essence of this literature succinctly: "The overreaction evidence shows that… security prices overreact to consistent patterns of news pointing in the same direction. That is, securities that have had a long record of good news tend to become overpriced and have low average returns afterwards… Securities with strings of good performance… receive extremely high valuations, and these valuations, on average, return to the mean."[4] We propose that

measures focus on short-term transactional exposures as opposed to trying to understand the competitive effects that macroeconomic variables entail. Oftentimes, the most extensive reporting concerns the derivatives that have been put in place to manage these exposures.

[3] Zoom is a useful example of excessive extrapolation of current growth trends. As the pandemic took hold, Zoom's share price exceeded $500. When the pandemic later receded, the price fell to below $100.

[4] In valuation textbooks, this is referred to as the "treadmill effect": high growth rates decay quickly because markets become saturated and competition sets in. The valuation mistake is to assume that they will remain high for much longer than is realistic, i.e. the analyst underestimates the decay rate of growth. If an analyst assumes 7% growth in perpetuity, whereas the real economy grows by 2-3%, this is akin to assuming that the focal firm will eventually become larger than the economy.

macroeconomic noise can generate a beneficial impact that seems to indicate that the firm's value drivers develop more positively than warranted by fundamentals, leading to overpricing and low subsequent returns.

Testing whether the market overreacts to macro-induced headwind or tailwinds requires us to quantify macroeconomic noise at the firm level. To achieve this, we apply the methodology developed by Oxelheim and Wihlborg (2008), which estimates corporate exposure through multiple regression rather than a "bottom-up" analytical approach. Each firm's quarterly earnings before interest and taxes (EBIT) are regressed on key macroeconomic variables, yielding exposure coefficients that indicate how EBIT on average responds to changes in these factors. By combining these coefficients with actual changes in exchange rates, interest rates, and inflation, we can quantify the contribution of macroeconomic luck to each firm's quarterly performance. Firms in the top third for positive impact are categorised as experiencing a tailwind, while those in the bottom third face a headwind.

Supporting the overreaction hypothesis, our research provides clear and compelling evidence that the market misprices macroeconomic noise. Specifically, we find that macroeconomic tailwinds lift stock prices in the current quarter but negatively predict prices two or three quarters later, while headwinds show the reverse pattern. This aligns with the concept of a temporary mispricing, followed by a correction when the effects of luck prove to be short-lived.

The influence of macroeconomic luck is first demonstrated through Fama-MacBeth regressions, which show that firm-quarters experiencing a tailwind outperform by approximately 8% on an annualised basis, all else being equal. Conversely, a headwind has a similarly sized but negative impact on stock returns. To investigate whether this impact is followed by a reversal, we apply the empirical approach from Barrot et al. (2016) and find that lagged tailwind (headwind) negatively (positively) predicts future accumulated returns beyond the present quarter. These findings strongly suggest a pattern in which the market initially overreacts to tailwind effects, only to correct when these effects prove unsustainable.

Reversals in performance typically do not occur in the quarter immediately following a tailwind or headwind but are more pronounced about two quarters later. This delay is due to the fact that during our sample period macronoise exhibits a certain positive autocorrelation of order one. Capturing profits from the luck effect within the current quarter may therefore be challenging. However, it is possible to create a portfolio strategy that leverages temporary misvaluations and their predictable reversals, whilst taking macro momentum into account. A strategy that goes long on stocks facing headwinds and short on those benefiting from tailwinds two quarters earlier yields annualised excess returns of close to 10%.

The immediate stock price windfall in the current quarter is significantly greater than what would be justified by the implied cash dividend from macroeconomic luck. It is important to see that the positive impact of tailwind on stock price is partly warranted by the dividend effect created by the noise. However, the implied cash effect suggests an annualised return of about 3.7%, whereas the actual annualised return in tailwind-affected quarters is closer to 6%.[5] We argue that this difference reflects a valuation error resulting from the capitalization of macroeconomic noise.

We further argue that misvaluations driven by macroeconomic luck are unevenly distributed across investor categories. More sophisticated and financially literate investors are less likely to interpret these signals as indicators of sustainable performance. Retail investors, by contrast, often have less training in financial analysis and are therefore less equipped to distinguish between the effects of temporary luck and

[5] The total positive contribution of macroeconomic noise to EBIT for tailwind-affected companies is, on average, NOK 5.7bn measured over a quarter. The total market capitalization of these companies is, on average, NOK 613bn. This implies a return of 5.7/613=0.65%, or 3.7% on an annualised basis.

genuinely sustainable gains. Thanks to a novel and granular dataset on Norwegian corporate ownership we are able to investigate the net trading of various investor categories in response to luck-induced additions to performance. Uniquely, this dataset allows us to track the net trades of all investors in the Norwegian market - both individuals and legal entities - on a daily basis.

Our findings support the notion that retail investors and sophisticated institutional investors react differently to macroeconomic luck. After accounting for retailers' well-documented contrarian tendencies, we find that they tend to buy into the effects of luck, whereas institutions tend to sell. This net buying leaves retail investors vulnerable to the eventual price reversal, while institutions appear to exit their positions before the correction occurs. This behaviour is most evident among foreign institutions, with domestic institutions showing it to a lesser extent. Grinblatt and Keloharjo et al. (2000) observe that foreign institutions achieve the highest trading gains of all investors in their Finnish dataset. As per our data, one possible source of these trading gains is foreign institutions' superior ability to assess how macroeconomic conditions impact corporate performance across countries.

This article primarily contributes to the asset pricing literature by introducing macroeconomic luck as a previously undocumented factor. Our results relate to prior studies showing that earnings quality has a predictable relationship with stock returns (Sloan, 1996; Xie, 2001; Dechow and Dichev, 2002). In particular, low-quality accruals are associated with negative future returns (Richardson et al., 2005; Francis et al., 2005). The prevailing explanation is that investors misinterpret accruals as genuine earnings, leading to a temporary overvaluation of firms with low-quality accruals. Macroeconomic noise can also be thought of as reducing the quality of earnings (in the case of tailwind), inducing an overvaluation. However, accruals result from managerial choices and can still signal future earnings potential.[6] By contrast, macroeconomic noise is externally determined and provides no insight into a firm's future earnings power, and therefore makes for a cleaner test of the overreaction hypothesis.

We also contribute to the overreaction hypothesis more broadly. Since De Bondt and Thaler (1985, 1987), researchers have investigated investors' tendency to overreact to news. This literature has documented a pattern of short-term momentum and longer-term reversals driven by various cognitive biases and emotional responses (De Bondt & Thaler, 1985, 1987; Jegadeesh & Titman, 1993, 2001; Barberis, Greenwood, Jin, and Shleifer, 2018). "Extrapolative expectations", in other words believing that recent trends will continue even if fundamentals do not justify it, are also well supported by surveys and experimental data (Smith et al, 1988; Haruvy et al, 2007; Greenwood & Shleifer, 2014). We add to this literature by showing that there is a distinct "macro-momentum", coupled with a later reversal towards the mean, that adds to the dynamics in stock markets.

Finally, our findings also add to the literature on investment behaviour. Since Grinblatt and Keloharjo (2000), research has shown that retail investors display a strong contrarian tendency, while institutional investors lean toward momentum trading. We extend this line of inquiry by revealing that retail and institutional investors also respond differently to noise in the market (whilst controlling for their contrarian and momentum tendencies.) Specifically, retail traders tend to buy stocks benefiting from macroeconomic luck, while foreign institutions are more likely to sell. Quite literally, retail investors act as noise traders. This behaviour aligns with prior research indicating

[6] The literature on accruals distinguishes between total and abnormal (discretionary) accruals. According to Xie (2001), abnormal accruals are less persistent, in other words, less informative about future earnings than total accruals. The mispricing of abnormal accruals is therefore higher due to the markets naive "fixation" on reported earnings. Macroeconomic luck is even less persistent. We show that there is a certain macro-momentum extending into the next quarter but apart from this, spells of macroeconomic luck are random and short-lived. In Xie's study, the earnings of the high-accrual cohort have not fully reverted to mean until three years after.

that retail investors are more prone to overreact to attention-grabbing media and sentiment-driven news (Barber and Odean, 2008; Tetlock, 2007; Han and Kumar, 2013; Barber et al. 2022).

2. Data and variables

Datasets

The dataset for this study integrates information from three sources: the Compustat Global Database (quarterly financial statements), Capital IQ (macroeconomic time series), and detailed corporate ownership records for investor classification. The sample consists of companies domiciled in Norway over the period 2004–2023.

Norway is a good case country for our study given its export-dependent economy. Norwegian firms were mainly selected, however, due to the availability of reliable measures of aggregate ownership by investor categories, leveraging data from the Norwegian Central Securities Depository (Verdipapirsentralen, VPS). VPS is Norway's central institution for securities registration and management. It plays a pivotal role in financial market infrastructure by providing services such as registration, clearing, and settlement of securities trades.

The VPS ownership data offers daily records of investor holdings for every publicly listed company in Norway. These holdings are classified into more than 20 investor types, including "private individuals" (retail investors), identified by personal number, and institutions. Changes in these holdings provide a daily measure of net trading activity for each investor type. In terms of granularity and investor identification, the VPS data resembles the Finnish dataset that has been utilised in several academic studies (Grinblatt and Keloharju, 2000; Grinblatt, Keloharu, Linnainmaa, 2011; Grinblatt, Keloharju and Linnainmaa, 2012.) The Norwegian VPS data has also been used by Betermier et al. (forthcoming) and Knüpfer et al. (2024) among others.

Macroeconomic luck

To estimate corporate exposure to macroeconomic risks, we adopt the methodology of Oxelheim and Wihlborg (2008). This approach involves regressing corporate performance metrics on macroeconomic variables such as exchange rates, interest rates, and inflation rates. As previously discussed, in this approach macroeconomic magnitudes such as GDP, productivity growth, and aggregate demand are "filtered through" to corporate exposure models through these readily observable changes in various market prices and rates.

The coefficients from such a regression on a firm's performance indicate how sensitive it is, on average, to changes in the macroeconomic environment. Importantly, firms are not only affected by direct translation effects stemming from the conversion of foreign currencies. They may also face significant competitive pressures due to the influence of macroeconomic variables on relative prices across industries and countries. Deviations from International Fisher Parity and Purchasing Power Parity shape excess profit and losses as some countries. Therefore, even firms operating exclusively domestically can still have considerable exposure to macroeconomic conditions. Also, there may be significant commercial exposure resulting from changes in interest rates, especially for firms selling capital intensive or luxury products (Oxelheim et al., 2010).

Earnings Before Interest and Taxes (EBIT) is chosen as the dependent variable because it captures a firm's operating performance, including its full cost structure. The literature on corporate exposure to macroeconomic risk emphasises that the variable selection and multivariate analysis should be preceded by a fundamental analysis of the firm's main commercial exposures (Oxelheim and Wihlborg, 2008). However, due to time constraints we adopt a more general approach and use the same set of variables for all firms. The baseline model regresses quarterly changes in EBIT on changes in the following key macroeconomic variables for the Norwegian corporate sector:

- *NOK/USD* and *NOK/EUR* exchange rates, reflecting Norway's export-dependent corporate sector.
- *Brent crude*, given the importance of oil to Norway's economy and its correlation with energy input costs.
- *Euribor* (short-term interest rates), relevant for aggregate demand and financing costs, especially for capital-intensive industries.

The exposure model is as follows:[7]

$$\Delta \mathrm{EBIT}_{it} = \beta_0 + \beta_1 \Delta \mathrm{Brent}_{it} + \beta_2 \Delta \mathrm{USD}_{it} + \beta_3 \Delta \mathrm{EUR}_{it} + \beta_4 \Delta \mathrm{Euribor}_{it} + \varepsilon_{it} \quad (Eq.1)$$

The exposure model in Eq. 1 is estimated for each firm on a rolling five-year window of quarterly observations, beginning in Q1 2009, as quarterly financial data is available from 2004 onward. Coefficients are retained only if their p-value is below 0.2. For each firm-quarter, the macro impact on performance is computed by multiplying each significant coefficient by the corresponding out-of-sample change in the macroeconomic variable and summing the results.[8] In Eq. 1 the simplifying assumption

[7] In the literature, corporate exposure is understood as unexpected changes in performance resulting from unexpected changes in macroeconomic variables. We leave out the expectation operators in Eq. 1 for ease of exposition.

[8] For example, if the coefficients for NOK/USD, Brent, and Euribor are 375, -29, and 1850, respectively, and the change in these variables in the relevant quarter is 0.25, -4, and 0.01, the macronoise would be 375 x 0.25 + (29) x (-4) + 1850 x 0.01 = 228 (NOK million). This would suggest that this firm has benefited from significant tailwind.

is made that all changes in macroeconomic variables are unexpected. Meese and Rogoff (1973) and later research (e.g. Rossi, 2013) have shown that short-term exchange rates are largely unpredictable ex-ante, and that econometric models do not generally improve on the random walk assumption in out-of-sample tests.

This procedure allows us to isolate the impact of macroeconomic factors from a firm's sustainable underlying performance. The macroeconomic contribution is then normalised by revenue to generate a variable called *Macronoise*. Two indicator variables are created based on this measure: *Tailwind*, which takes the value 1 if Macronoise is in the top tercile for the quarter, and *Headwind*, which takes the value 1 if Macronoise is in the bottom tercile for the quarter.

Investor type

The ownership lists from VPS indicate whether each owner is an individual or a legal entity. Furthermore, they indicate the nationality of the investor and its sector code. We utilise this information to create the following variables:

- *MicroRetail*: The sum of all ownership stakes smaller than 0.01% held by private individuals, divided by the total number of shares
- *MediumRetail*: The sum of all ownership stakes between 0.01% and 1% held by private individuals, divided by the total number of shares
- *Institutions*: The sum of all ownership stakes held by mutual funds, pension funds, savings banks, and foundations, divided by the total number of shares.
- *ForeignInst*: The sum of all ownership stakes held by foreign institutions, divided by the total number of shares.

Returns are calculated as the percentage change in the stock price, adjusted for dividends and stock splits. We complement the macro and ownership variables two control variables from the literature: *Profitability*, defined as EBIT/Assets, and *MarketCap*, defined as the log of market capitalization. Returns and Profitability are winsorised at the 2nd and 98th percentiles.

2. Empirical analysis

Descriptive statistics

Table 1 presents the descriptive statistics of the variable used in this study.

INSERT TABLE 1 ABOUT HERE

The average of Mnoise is close to zero and appears largely symmetric around the mean. The standard deviation is 0.1, indicating that the contribution of macro factors to profits (EBIT) equals or exceeds 10% of revenue in approximately one-third of firm-quarters. These figures suggest that macroeconomic "luck" plays an economically significant role in corporate performance. Reflecting their definitions based on terciles, the averages of Headwind and Tailwind are 33%.

An interesting feature of both Macronoise and its normalised counterpart Mnoise is that they display a positive autocorrelation of order one.[9] That is, tailwind in the

[9] The autocorrelation at lag 2 is however only 0.18 so the variable is not non-stationary and can hence be included in the regression model without taking first differences. This is confirmed by both the (panel versions) of the Dickey-Fuller and Phillips-Perron tests for stationarity that reject the null of a unit root with p-values < 0.001.

preceding quarter positively predicts tailwind in the next. This "macro momentum" can be traced back to a positive autocorrelation (when measured in first differences) for all the four macro variables in the exposure model. While the lag structure is not identical for the different variables, it is generally only the preceding quarter that is significant. This suggests that the positive effects of macroeconomic tailwind may partially "linger" into the following quarter.

Table 2 reports Pearson correlations. We note that Mnoise displays a positive correlation with Profitability. This correlation arises naturally because macroeconomic noise is embedded in the earnings numbers. That is, positive values of Mnoise have boosted the earnings that get reported in that quarter, whereas negative ones have reduced it.

Fama McBeth regressions

To assess how macroeconomic noise relates to stock returns, we begin by implementing monthly Fama and McBeth (1973) regressions. The complete specification is as follows:

$$\text{Return}_{it} = \alpha_i + \beta_1 \text{Mnoise}_{it} + \beta_2 \text{Profitability}_{it} + \beta_3 \text{MarketCap}_{it} + \beta_4 \text{Return\_L}_{it} + \varepsilon_{it} \quad (Eq.2)$$

Alternatively, we replace Mnoise with the binary variables Tailwind and Headwind to get a more easily interpretable estimate of the impact of favourable or unfavourable macroeconomic luck. In these cases, Tailwind and Headwind lagged 1, 2, and 3 quarters are included in order to explore whether past luck predicts returns. In Eq.2, Momentum effects are controlled for by including lagged values of stock return

(Return_L). MarketCap and Profitability are included to control for size and profitability effects.

Table 3 reports the results of the Fama McBeth regressions. Model 1 shows the results using Mnoise, and Models 2 and 3 show the corresponding models where Tailwind and Headwind replace Mnoise, respectively. As can be seen, both Profitability, MarketCap, and momentum are statistically significant in predicting returns. The coefficient on Mnoise loads positively, suggesting that favourable macroeconomic conditions indeed give a boost to the share price. Confirming this relation, Tailwind (Headwind) predicts a negative (positive) effect on stock prices. The coefficients imply an annualised incremental stock return of 8.73% in the case of tailwind, and -5.67% for headwind.

Barrot et al regressions

To assess whether the impact of macroeconomic luck on stock returns tends to be reversed over time, we implement the empirical model in Barrot et al (2016). This model predicts accumulated future returns as a function of luck in the current period whilst controlling for past returns.[10] The full specification is as follows:

$$\text{Return}_{i,t_1,t_2} = \alpha_i + \gamma_t + \beta_1 \text{Mnoise}_{i,t} + \beta_2 \text{Profitability}_{i,t} + \beta_3 \text{MarketCap}_{i,t} + \beta_4 \text{Return\_L}_{i,t} + \varepsilon_{i,t} \quad (Eq.3)$$

[10] The purpose of the analysis in Barrot et al is to gauge whether net buying or selling by retailers predict future returns. Past returns are included to control for momentum effects.

We modify the specification compared to Barrot et al (2016) in that we begin accumulating returns only after the first three months. This is because we know from the previous section that tailwind predicts returns in the current quarter positively. If a reversal is taking place, the initial positive returns and the later negative ones would tend to cancel each other out. Instead, we analyse the first three months separately, and start accumulating returns after that (in the fourth month). Table 4 reports the results. In Model 1, for comparison, the returns are accumulated over the first two months. In Models 2 through 8, returns are accumulated as of the fourth month, with the ending month set to values between 6 and 12.

INSERT TABLE 4

The results in Table 4 clearly speak to a reversal following the initial windfall. Model 1 confirms the boost provided by macroeconomic luck indicated in the previous section. The coefficient on Tailwind is positive and significant at the 5%-level. The coefficient in Model 2 is negative, however, albeit not significantly so. For each month that gets added, the significance level improves and reaches its highest level for Model 5 (in which the dependent variable sums the returns between months 4 and 9. After that, the significance level tapers off to eventually become insignificant in Model 10. That the significance disappears is only to be expected, because the further out in time we move, the signal from the macroeconomic noise is overwhelmed by other factors influencing stock returns. Strikingly, in Models 2-10 the coefficient on Tailwind is consistently negative, in sharp contrast to the initial boost it provides in the near-term.

Portfolio sorts

The analyses in the previous two sections suggest that it might be possible to trade profitably on macroeconomic luck. While the tailwind or headwind in the current quarter could be difficult to assess and exploit, the reversal might be more amenable to trading strategies. In this section, we test a portfolio strategy that goes long on stocks that have faced headwind and goes short on stocks that have benefited from tailwind, on the logic that headwind (tailwind) is conducive to temporary undervaluations (overvaluations.)

Table 5 presents the results from the "macroluck" long-short strategy. In order to not have the strategy be contaminated by macro momentum, the sorting is done based on the headwind or tailwind measured two quarters prior. In Model A, abnormal returns are calculated relative to the Fama and French 3-factor model (Fama and French, 1993). There is a concern, however, that any excess return on the macroluck portfolio could be driven by an implied risk premium on the macroeconomic variables that were used to filter out the noise from performance. After all, Norway is disproportionally reliant on exports, which could make it hard for investors to diversify away macroeconomic risk. In Model B, we therefore include the returns on the macroeconomic variables. Moreover, one might argue that our proxy for macroeconomic luck is based on corporate fundamentals, which introduces the possibility that it is systematically related to two other commonly used factors, namely those included in the Fama and French (2015) 5-factor model. To mitigate this concern, Model 5 adds the profitability and investment factors. According to Table 5, the macroluck strategy produces annualised gains that range between 7% and over 10% in the full specification..

Macroeconomic luck and investor behaviour

Investors may respond differently to macroluck depending on their financial literacy. Somebody well versed in financial analysis might be less easily fooled by the transient effects induced by macro variables. In the literature, institutional investors are usually thought to have a higher level of analytical skills, as well as more resources compared to retailers acting on their own behalf. In their seminal paper, Grinblatt and Keloharjo (2000) documented clear differences in styles and trading gains across different investor categories. The highest and most consistent gains in their sample were achieved by foreign institutions, presumably due to their considerable sophistication in investment analysis. Retailers, in contrast, perform less well, partly due to a contrarian tendency that causes them to miss out on momentum effects. While the debate on retailers' performance is still ongoing, there is plenty of research showing that they are more prone to various kinds of investment mistakes.

Against this backdrop, we ask the question of whether retailers are more prone than other investors to buy into macroeconomic tailwind (luck), mistaking it for sustainable profits. Such a tendency would be problematic because it exposes them to the reversal that tends to follow. To learn more about how different investor classes respond to macroluck, we estimate regressions in which macroeconomic noise is the independent variable and the change in aggregate ownership (per investor category) is the dependent. Because the ownership variables are only available between november 2019 and december 2022, we use the normalised measure of macroeconomic luck (Mnoise) to exploit the full variation in this variable.

Table 6 reports the results. The four models are lined up according to increasing degree of presumed sophistication (MicroRetail, MediumRetail, Institutions (domestic) and ForeignInst.) For MediumRetail, the coefficient on Mnoise is positive and significant at the 5% level. This suggests that retailers "buy luck" in the sense of investing more when the company's results are helped along by random factors. MicroRetail, however, shows no clear tendency. A possible explanation is that micro retailers do not rely to the same extent on financial numbers in the first place. That is, they are more prone to act according to simple heuristics that do not necessarily refer to financial information, like "buy the dip" or other pattern-exploiting strategies referring only to stock prices themselves. MediumRetailers are more likely to incorporate firm fundamentals into their analysis and thus be more attentive to things like EBIT growth. Ironically, being somewhat more sophisticated in this regard sets them up for the investment mistake that occurs when one is unable to distinguish between macro-induced growth and its organic counterpart.

As for the institutions, the coefficient on Mnoise is insignificant in the case of domestic institutions, but negative and significant for ForeignInst (albeit only at the 10% level). The explanation for this could be that foreign institutions are highly sophisticated in terms of their trading strategies, as suggested by the analysis in Grinblatt and Keloharjo (2000). Thanks to their international presence, they might be particularly well placed to interpret and understand the role of macroeconomic factors in driving the relative performance of different sectors.

4. Conclusions

According to the efficient market hypothesis, investors are supposed to price financial assets in such a way that their current market price reflects all available information. Macroeconomic noise presents a challenge to this hypothesis because it comes "in disguise", superficially indistinguishable from the very value drivers the market is supposed to derive its prices from (growth and profitability). Making this setting even more compelling is the fact that valuation experts single out the extrapolation of past growth rates into the future as *the* valuation error. If recent financial performance is inflated by macroeconomic luck, all the conditions for a temporary mispricing of stocks are present.

In this research, we have shown that the market seemingly fails at the task of separating macroeconomic luck from genuine and more sustainable performance. Tailwind gives a boost to the share price in the present quarter, over and beyond what is warranted by the cash dividend it implies. Aside from a one-quarter "macro-momentum", in other words the fact that macro variables display an autocorrelation of order one, macro effects on corporate performance are largely random and transient. Across different methodological approaches, we find clear evidence of a reversal of the initial mispricing taking place in the quarters following the luck-impacted quarter. A portfolio strategy designed to capitalise on the temporary mispricing (long on headwind and short on tailwind) yields annualised excess returns of about 10%.

The implication for investors is that they should pay more attention to how the current macroeconomic environment is driving corporate performance. While corporate disclosure of such exposures tends to be partial and otherwise flawed, the relation between macro factors and firm-level measures like EBIT can be approximated using statistical models, as demonstrated in the pioneering work by Oxelheim and Wilhborg (2008). Such methods allow investors to quantify macroeconomic luck and make sure that only "macro-adjusted" estimates of profitability and growth are fed into their models. Future research could shed light on the link between macroeconomic noise and the consensus forecasts produced by analysts, as they are an important mediator between corporate fundamentals and asset prices.

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Appendix

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
MacroNoise	12404	0.001	0.103	-0.358	0.399
Tailwind	12490	0.334	0.472	0.000	1.000
Headwind	12404	0.330	0.470	0.000	1.000
Return	17825	0.006	0.125	-0.300	0.396
Profitability	14559	0.012	0.092	-0.339	0.208
Market Cap	17483	7.697	1.957	1.013	14.016

Table 2 Correlation table

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) MacroNoise	1.000					
(2) Tailwind	0.505*	1.000				
	(0.000)					
(3) Headwind	-0.501*	-0.496*	1.000			
	(0.000)	(0.000)				
(4) Return	0.017	0.009	-0.038*	1.000		
	(0.060)	(0.344)	(0.000)			
(5) Profitability	0.054*	-0.042*	-0.173*	0.080*	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)		
(6) Market Cap	0.019	-0.058*	-0.045*	0.061*	0.334*	1.000
	(0.039)	(0.000)	(0.000)	(0.000)	(0.000)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3 Macroeconomic luck and returns

	(1)	(2)	(3)
	Model_1	Model_2	Model_3
MacroNoise	.067**		
	(.027)		
Headwind		-.004*	
		(.003)	
Tailwind			.005**
Return_l1	-.006	-.003	-.004
	(.014)	(.014)	(.014)
Return_l2	.046***	.04***	.043***
	(.013)	(.013)	(.013)
Return_l3	.029**	.03**	.03**
	(.015)	(.015)	(.015)
Return_l4	.018	.018	.018
	(.014)	(.014)	(.014)
Profitability	.113***	.118***	.122***
	(.034)	(.033)	(.033)
Market Cap	.002***	.002**	.002***
	(.001)	(.001)	(.001)
Constant	-.007	-.006	-.011*
	(.006)	(.006)	(.006)
Observations	11731	11731	11731
R-squared	.185	.177	.175

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 5 Macroluck and future returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	F2/2	F6/4	F7/4	F8/4	F9/4	F10/4	F11/4	F12/4
Tailwind	.01**	-.007	-.01	-.015	-.021**	-.023**	-.022*	-.02
	(.004)	(.007)	(.008)	(.009)	(.01)	(.012)	(.013)	(.014)
Market Cap	-.035***	-.058***	-.077***	-.097***	-.116***	-.135***	-.155***	-.174***
	(.005)	(.007)	(.01)	(.012)	(.015)	(.017)	(.019)	(.022)
Profitability	.25***	.237***	.274**	.275**	.264*	.283*	.305*	.349*
	(.048)	(.083)	(.111)	(.134)	(.153)	(.169)	(.184)	(.2)
Return	.03*	.04*	.05**	.072***	.108***	.125***	.138***	.156***
	(.017)	(.022)	(.024)	(.024)	(.024)	(.027)	(.032)	(.035)
Return_l1	.059***	.029	.05***	.087***	.107***	.123***	.136***	.119***
	(.019)	(.018)	(.018)	(.021)	(.024)	(.029)	(.031)	(.031)
Return_l2	.059***	.054***	.088***	.11***	.134***	.145***	.133***	.143***
	(.016)	(.015)	(.016)	(.021)	(.026)	(.028)	(.027)	(.033)
Return_l3	.021	.064***	.085***	.105***	.116***	.101***	.109***	.125***
	(.016)	(.015)	(.021)	(.027)	(.028)	(.026)	(.031)	(.033)
_cons	.088**	.516***	.645***	.873***	1.036***	1.183***	1.332***	1.503***
	(.043)	(.054)	(.068)	(.089)	(.103)	(.122)	(.143)	(.161)
Observations	11530	11038	10933	10828	10723	10615	10507	10399
R-squared	.157	.158	.171	.18	.19	.196	.206	.214
Firm fixed	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed	NO	NO	NO	NO	NO	NO	NO	NO

*Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1*

Table 5 Long-short portfolio returns

	(1) Model_1	(2) Model_2	(3) Model_3
MKT	-.092	-.081	-.049
	(.084)	(.084)	(.086)
SMB	2.681	3.42	4.001*
	(2.274)	(2.286)	(2.312)
HML	-2.432	-2.807*	-3.247**
	(1.536)	(1.566)	(1.612)
Brent		-.055*	-.06**
		(.03)	(.03)
USD		.035	.009
		(.11)	(.112)
EUR		-.474**	-.443**
		(.184)	(.185)
Euribor		.001	0
		(.004)	(.004)
RMW			1.676
			(1.91)
CMA			2.87
			(1.919)
Constant	.006*	.009**	.008*
	(.003)	(.004)	(.004)
Observations	153	153	153
R-squared	.044	.093	.109

*Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1*

Table 6 Investor typ and macroluck

	(1)	(2)	(3)	(4)
	Microretail	MediumRetail	Institutions	ForeignInst
MacroNoise	-.02	.095*	.045	-.353*
	(.037)	(.052)	(.078)	(.182)
Market Cap	-.001	-.02***	.002	.031***
	(.001)	(.003)	(.005)	(.009)
Return	-.115**	-.451***	.228***	.939***
	(.056)	(.073)	(.076)	(.198)
Return_l1	-.04	-.078	.181**	.64***
	(.042)	(.06)	(.078)	(.151)
Return_l2	.006	-.058	.057	.264
	(.03)	(.054)	(.075)	(.165)
Return_l3	.043	-.051	.037	.206
	(.028)	(.06)	(.062)	(.144)
Constant	.068***	.144***	-.1*	.66***
	(.021)	(.053)	(.054)	(.161)
Observations	3529	3391	3043	3397
Pseudo R^2	.z	.z	.z	.z

*Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1*

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