Mispricing Proxies in Factor Models for Asset Returns

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ABSTRACT

This paper examines the influence of mispricing proxies on stock return dynamics within the framework of Fama–French five-factor models. Specifically, we assess the role of mispricing proxies derived from cointegration between asset prices and factor prices, as well as sentiment indicators extracted from quarterly earnings conference calls. Using quarterly data from 1980 to 2023 for the cross-section of DJIA-listed firms, our empirical analysis shows that deviations from long-run trends, driven by factor prices, have predictive power for stock returns after controlling for the five Fama–French factors. Stock-specific sentiment further enhances predictability. The additional predictability generated by mispricing proxies is fully explained by a nonlinear model in which sentiment determines the speed of adjustment toward the long-run trend identified by cointegration analysis when stock prices are above it.

CCS CONCEPTS

• **Applied computing** → **Economics**; • **Computing methodologies** → *Natural language processing*; • **Information systems** → Data mining.

KEYWORDS

factor models, mispricing, cointegration, sentiment measures, natural language processing, JEL C38, JEL G12, JEL G14, JEL G17

1 INTRODUCTION

Factor models decompose asset returns into compensation for common risk and an idiosyncratic component. Under no arbitrage, common risk is priced whereas diversifiable idiosyncratic risk is not. Deviations of expected returns from factor-implied values are therefore natural candidates for mispricing. Mispricing in factor models is often assessed through tests of whether intercepts in excess-return regressions are jointly zero [7]. Such tests capture average pricing errors but do not directly model stock-specific time variation. Stambaugh and Yuan [11] instead construct factors designed to capture mispricing and show that aggregate sentiment predicts these factors, especially the short legs of anomaly portfolios. Our approach differs by deriving the econometric proxy internally from the prices of the same factors used in the return model, and then combining it with firm-specific textual sentiment. We examine two stock-specific proxies for time-varying mispricing. A time-series approach to the relation between asset prices, factor prices, asset returns and factor returns derives our first proxy. We start from the intuition that asset prices are driven by a permanent and a temporary component, [4] and we build a model in which factor prices, i.e. the values of buy-and-hold portfolios in the 5 Fama-French factors [5], are used to capture the permanent component in asset prices. If this model is successful, then its residuals are stationary and mean-reverting and they can be intepreted as a proxy of mispricing,an Equilibrium Correction Term(ECT). The ECT is stationary and measures temporary over- or undervaluation and it becomes an additional regressor with a significant coefficient in the standard factor model. The second proxy is firm-level sentiment extracted with FinBERT from quarterly earnings-call transcripts [1]. Earnings calls offer repeated, company-specific communication and avoid the uneven news coverage received by different firms [8].

Our contribution is threefold. First, we construct an internally consistent mispricing proxy from the same factors used in the return model. Second, we combine this econometric proxy with a granular textual measure. Third, we show that sentiment is most informative through a nonlinear mechanism: favorable sentiment slows correction when prices are above their factor-implied trend. This mechanism is consistent with limits to arbitrage and diagnostic-expectations models, in which favorable signals can reinforce beliefs supporting an already elevated price [2, 3, 11].

Using quarterly observations through 2023 for a subset of DJIA constituents whose prices are cointegrated with factor prices, we obtain three principal findings. The ECT predicts subsequent returns negatively, sentiment predicts returns positively, and the two effects are economically and statistically significant under common-coefficient restrictions. In the nonlinear model, the independent sentiment coefficient becomes smaller, while sentiment significantly moderates the correction of overpricing. Detailed construction steps, individual-firm estimates, diagnostic figures, and robustness material are reported in the Web Appendix.

2 FRAMEWORK AND MISPRICING MEASURES

For stock i, the standard factor model is

$$r_{i,t+1} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_{t+1} + v_{i,t+1}, \tag{1}$$

where $\mathbf{f}_{t+1}$ contains the five Fama–French factors. If a factor model is interpreted in a no-arbitrage context, then it is evident that the total compensation for risk is decomposed two parts: a compensation for a common risk component, captured by the factors, and a compensation for an idiosyncratic risk component captured by the residuals from the projection of excess returns on factors. Common risk, being undiversifiable, needs a compensation while idiosyncratic risk, being diversifiable, does not need a compensation, therefore a common test for the validity of a factor model is performed by evaluating the null $\alpha = 0$. The reduction in dimensionality of the parameters in the variance-covariance matrix of returns occurs as a consequence of orthogonality between the common and the idiosyncratic risk components for all assets and of the orthogonality between the idiosyncratic risk components of all assets.

To empirically evaluate the potential role of mis-spricing in factor models consider the following general specification for each of the available n test-assets :

$$r_{i,t+1} = \alpha_i + \beta_i \mathbf{f}_{t+1} + \delta_i(L) u^{MP}_{i,t+1} + v_{i,t+1}, \quad \text{with } \mathbf{v}_{t+1} \sim \mathcal{D}\left(\mathbf{0}, \Sigma_{\mathbf{v}}\right) \tag{2}$$

where $u^{MP}_{i,t+1}$ represents the idiosyncratic variables that are candidates to capture mispricing in the standard factor model. Given the general specification and different variables candidate to capture mispricing, we shall also test the hypothesis that the response to mis-pricing is common across different assets, i.e. $\delta_i(L) = \delta(L)$.

2.1 Cointegration-based proxy

Mispricing proxies can be naturally derived by taking a cointegration-based approach to factor models Favero et al. [6]

Consider factor models specified on log excess returns and define log cumulative excess returns on asset i $\ln P_{i,t}$ as:

$$\ln P_{i,t} = \ln P_{i,t-1} + r_{i,t} \ , \tag{3}$$

i.e., (log)prices of any asset are cumulative (log) returns. The analogous of the (log) price for an asset can be constructed for any given factor.

Specifically, the generic factor prices associated with the log factor return $\mathbf{f}_t$ evolves according to the following process:

$$\ln \mathbf{F}_t = \ln \mathbf{F}_{t-1} + \mathbf{f}_t \ . \tag{4}$$

Test assets returns and factors are stationary, but asset prices and factor prices are non-stationary.

If factor prices are the non-stationary variables that drive the non-stationary dynamics of asset prices, then a linear combination of asset prices and factor prices should be stationary; i.e., asset and factor prices should be cointegrated.

Consider the following model describing the exposure of a given asset price $P_{i,t}$ to a given set of factor prices $\mathbf{F}_t$:

$$\ln P_{i,t+1} = \alpha_{0,i} + \alpha_{1,i} t + \beta_i' \ln \mathbf{F}_{t+1} + u_{i,t+1} \ , \qquad i = 1, \ldots, n \tag{5}$$
$$u_{i,t+1} = \rho_i u_{i,t} + v^r_{i,t+1}$$

If the residuals are stationary, i.e. $|\rho_i| < 1$, then we have cointegration between factors' and asset prices. In this case, $u_{i,t}$ captures temporary deviations of prices from the long-run value determined by the factor prices. Thus, it is natural to refer to $u_{i,t}$ as the “Equilibrium Correction Term" (henceforth, *ECT*) associated with asset i at time t.

$$ECT^P_{i,t} \equiv \ln P_{i,t} - \hat{\alpha}_{0,i} - \hat{\alpha}_{1,i} t - \hat{\beta}_i' \ln \mathbf{F}_t \ .$$

Interestingly, the existence of cointegration and therefore the stationarity of the ECT is naturally interpreted as an indication of validity of a factor models. The validity of a factor model can be judged by the capability of factor prices to capture the stochastic trend in asset prices. In fact, this argument could be further refined by imposing two requirements for a valid factor models: no-cointegration between factor prices (the presence of common trends among factors prices would be an indication of "redundancy of some of the factors") and cointegration between factor prices and asset prices.

2.1.1 *The Augmented Factor Model.*

The presence of cointegration generates a mispricing proxy in factor models.

By differencing (5) we see that cointegration between asset and factors prices implies the presence of a new additional predictive term in the standard factor model projection of returns on factors

$$r_{i,t+1} = \alpha_{1,i} + \beta_i' \mathbf{f}_{t+1} + \underbrace{(\rho_i - 1)}_{\delta_i} \underbrace{u^{CB}_{i,t}}_{\equiv ECT^P_{i,t}} + v^r_{i,t+1}, \tag{6}$$

Note that the presence of the mispricing term in standard factor models generated by the cointegration approach is ruled out only in the case of the presence of a unit root in the ECT term i.e. when there is no cointegration between asset prices and factor prices. By construction, the CB-based mispricing proxy affects asset returns with a one-period lag.

2.2 Sentiment-based Mispricing Proxies

An alternative mispricing proxy to the cointegration-based one has been developed, using a sentiment indicator constructed from the analysis of earnings call transcripts with natural language processing (NLP) techniques, specifically employing the FinBERT model. Earnings calls, where corporate executives discuss financial performance and future outlook, are valuable sources of information for investors. To distill insights from these complex and lengthy conversations, FinBERT, a model fine-tuned on financial data, was leveraged to extract sentiment from these texts and quantify the overall tone of the discussion. The process of constructing this sentiment indicator involved several steps, including data extraction, sentence-level sentiment scoring, and the final calculation of an overall sentiment score for each earnings call.

2.2.1 *Data Extraction and Preprocessing.*

The first step involved obtaining the earnings call transcript in a format suitable for sentiment analysis. The text was extracted and broken down into individual sentences, with each sentence serving as a unit of analysis. This granular approach allowed for a more detailed and accurate sentiment assessment. Once segmented, the data was converted into a structured CSV file. Each row contained a single sentence from the earnings call, which was then analyzed independently.

2.2.2 *Applying FinBERT for Sentiment Analysis.*

To evaluate the sentiment of each sentence, the FinBERT model was employed. FinBERT is a pre-trained transformer model specifically tailored for sentiment analysis in financial texts. Unlike general-purpose NLP models, FinBERT is fine-tuned on financial data, making it particularly effective in capturing the nuances of language used in the finance sector. Its training involved a large annotated dataset from the Financial Phrasebank, ensuring its ability to identify positive, negative, and neutral sentiments in the context of financial markets.

The Financial Phrasebank, developed as part of this research, is a collection of over 4,800 sentences annotated by financial experts. Each sentence is classified as positive, negative, or neutral based on its likely impact on stock prices from an investor's perspective. Sentences with annotations from at least 16 contributors form the basis for training FinBERT. This dataset is essential in ensuring that the model is fine-tuned specifically for the financial domain, where certain phrases or statements may carry sentiment that could easily be missed or misinterpreted by models trained on non-financial data.

Using FinBERT, each sentence in the earnings call transcript was processed, and a sentiment score was assigned based on FinBERT's analysis. The model categorizes sentences into three categories: positive, negative, or neutral. Positive sentences typically highlight favorable financial performance or optimistic future outlooks, while negative sentences focus on challenges, losses, or unfavorable trends. Neutral sentences, on the other hand, do not present any clear sentiment relevant to financial outcomes.

2.2.3 *Calculating the Overall Sentiment Indicator.*

Once each sentence was associated with a sentiment score, the overall sentiment for the entire earnings call was calculated. This step involves aggregating the sentence-level scores to provide a single summary metric representing the tone of the call. To compute this, the average of the individual sentiment scores was taken, giving equal weight to each sentence. The resulting outcome serves as the final sentiment indicator for the earnings call, offering a snapshot of the call's overall sentiment—whether positive, negative, or neutral.

2.2.4 *The Financial Phrasebank.*

The accuracy of FinBERT's sentiment scoring can be attributed to the Financial Phrasebank, which plays a critical role in ensuring that the model is finely attuned to the language used in financial communications. The Phrasebank contains sentences that were manually annotated by finance students and researchers with relevant domain knowledge, ensuring that the resulting model captures the specific nuances of financial language. The dataset offers multiple agreement levels for annotations—ranging from 100% consensus to 50% majority voting—providing flexibility in building sentiment models. For this sentiment indicator, using sentences with high agreement ensures a more reliable and consistent interpretation of sentiment.

The Financial Phrasebank focuses specifically on sentences that influence stock prices from an investor's perspective. This domain-specific annotation enables FinBERT to accurately assess how a given sentence, and by extension, the entire earnings call, might affect investor sentiment and market behaviour. Sentences that may appear neutral or irrelevant to non-financial models are carefully evaluated in terms of their potential impact on stock prices, significantly enhancing the model's applicability to real-world financial analysis.

2.2.5 *Example: JPM Sentiment Indicator.*

This section presents an example for JPMorgan Chase (JPM). The following time series illustrates the sentiment scores for multiple earnings calls, highlighting the minimum and maximum sentiment scores.

Below are the two earnings call transcripts corresponding to the minimum and maximum sentiment scores for JPM. The left image shows the earnings call with the minimum sentiment score, while the right image shows the call with the maximum sentiment score.

In conclusion, using FinBERT, the Financial Phrasebank and by breaking down the text into individual sentences and applying a financial-domain-specific NLP model, an accurate sentiment score was generated that reflects the overall tone of the call. This sentiment indicator gauges the mood of corporate executives during earnings calls, helping to inform investment decisions. By leveraging FinBERT's specialized training and the comprehensive annotation of the Financial Phrasebank, the resulting sentiment scores offers a measure of financial sentiment in earnings calls.

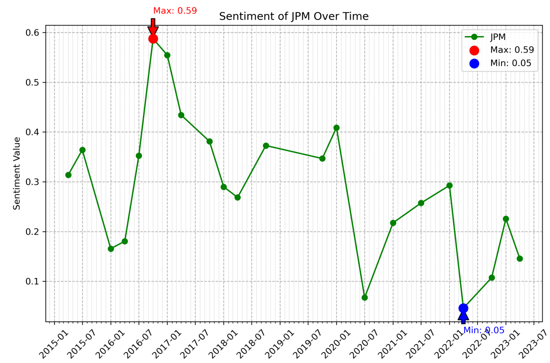

Figure 1: JPM Sentiment Scores for Earnings Calls

2.2.6 *The augmented factor model specification.*

In the case of sentiment based mis-pricing proxies, the relevant augmented factor model will be the following:

$$r_{i,t+1} = \alpha_{1,i} + \beta_i' \mathbf{f}_{t+1} + \delta_i u_{i,t+1}^{SB} + \ v_{i,t+1}^{r}, \tag{7}$$

where $u_{i,t+1}^{SB}$ are the asset specific sentiment-based mis-pricing proxies. Note that, while the econometric specification strategy leads to the inclusion in the specification of the cointegration based proxy with a lag, the sentiment based proxy is simply an additional variable that affects returns contemporaneously as the factors. Both the CB-based and the SB-based proxy are idiosyncratic to test assets and are meant to capture fluctuations in the idiosyncratic risk components, but the timing of the CB based proxy is different because of the link between cointegration between asset prices and factor prices and the implied Equilibrium Correction Term for asset returns.

16	Regarding loan growth, we're continuing to see positive trends with loans up 8% year-on-year and 1% quarter-on-quarter ex PPP with the sequential growth driven by a continued pickup in demand in our Wholesale businesses, including ongoing strength in AWM.	1
17	On Page 2, we have some more detail on our results	-1.40E-06
18	**Revenue** of $31.6 billion was **down $1.5 billion or 5% year-on-year**	-0.99999744
19	NII ex Markets was up $1 billion or 9% on balance sheet growth and higher rates, partially offset by lower NII from PPP loans	0.99994177
20	**NIR ex Markets was down $2.2 billion or 17%** predominantly driven by lower IB fees, lower Home Lending production revenue, **losses in Credit Adjustments** & Other and CIB as well as **investment securities losses** in corporate	-0.99998677
21	And **Markets revenue was down $300 million or 3%** against a record first quarter last year.	-0.9999984
22	Expenses of $19.2 billion were up approximately $500 million or 2% predominantly on higher investments and structural expenses, largely offset by lower volume and revenue-related expenses	0.8322505
23	Credit costs were $1.5 billion for the quarter	-0.000568593
24	We built $902 million in reserves driven by increasing the probability of downside risks due to high inflation and the war in Ukraine as well as builds for Russia-associated exposures in CIB and AWM.	0.004683026
25	Net charge-offs of $582 million were down year-on-year and comparable to last quarter and remain historically low across our portfolios.	-0.99884903
26	On to balance sheet and capital on Page 3	-3.66E-06
27	Our **CET1 ratio** ended at 11.9%, **down 120 basis points from the prior quarter**	-0.9987935
28	As a reminder, we exited the fourth quarter with an elevated buffer to absorb anticipated changes this quarter, the largest being SA-CCR adoption as well as some pickup in seasonal activity.	0.3082016
29	In addition to those anticipated items, there were a couple of other drivers	-0.012411644
30	The rate sell-off led to AOCI drawdowns in our AFS portfolio	-0.07326184
31	But keep in mind, all else equal, these mark-to-market losses accrete back to capital through time and as securities mature	-0.006182162
32	And price increases across commodities resulted in higher counterparty credit and market risk RWA.	0.62100106
33	While, of course, the **environment is uncertain**, many of these effects are now in the rearview mirror	-0.8923381
34	And as a result, we believe that our current capital and future earnings profile position us well to continue supporting business growth while meeting increasing capital requirements as we look ahead.	1
35	With that, let's go to our businesses, starting with Consumer & Community Banking on Page 4	-1.71E-06
36	CCB reported **net income** of $2.9 billion on revenue of $12.2 billion, which was **down 2% year-on-year**	-0.9999996
37	In Consumer & Business Banking, revenue was up 8% predominantly driven by growth in deposit balances and client investment assets, partially offset by deposit margin compression.	0.9999978
38	Deposits were up 18% year-on-year and 4% quarter-on-quarter, consistent with last quarter	0.99992645
39	And client investment assets were up 9% year-on-year largely driven by flows in addition to market performance.	0.9999981
40	In Home Lending, **revenue was down 20% year-on-year** on **lower production revenue** from both **lower margins and volumes** against a very strong quarter last year, largely offset by higher net servicing revenue	-0.99999887
41	**Originations** of $24.7 billion **declined 37% with the rise in rates**	-0.999426
42	And as a result, **mortgage loans were down 3%.**	-0.9985784

(a) Earnings Call with Min Sentiment

15	Starting on page 1 and taking a look at the quarter we had **strong performance in each of our businesses** despite the continuation of reasonably challenging conditions.	0.9999998
16	Bringing it all together this quarter's result was clean with no significant items and with the firm reporting net income of $6.3 billion, EPS of $1.58 and the return on tangible common equity of 13% on $25.5 billion of revenue	0.9730507
17	Highlights of the quarter include the **highest reported revenue for a third quarter in CIB** with **IBCs up 15%** and **markets revenues up 33%** with **strong performance across the board**.	1
18	**Robust core loan growth** for the Company of **15%** on the back of **sustained demand across businesses**	1
19	And the **continuation of strong credit performance** including a net release for Oil & Gas.	1
20	**Card sales are back to double-digit growth** year on year and we saw a strong positive market reaction to new proprietary products	1
21	Finally, we had record **consumer deposit growth up 11%.**	1
22	Before I move on we recently submitted our 2016 resolution filing	-1.28E-05
23	The Board and management believes that we submitted a credible plan and **more than met the requirements** for the October submission	0.99812907
24	It was a tremendous effort across the Company involving all businesses and functions and we took many significant actions, perhaps most notably **improving the firm's overall liquidity** and pre-positioning our material legal entities for both liquidity and capital.	0.99999994
25	We determined this is in the best interest of the Company, albeit at some cost	-0.018679436
26	We took many other important actions which hopefully you've had the chance to review in our public filings.	0.000510423
27	Moving back to the quarter and moving on to page 2 **revenue** of $25.5 billion was up $2 billion year on year or **up 8%**	0.99937934
28	On the back of **continued strong growth in core loans net interest income was up** $700 million and is trending for the full year to be above the $2.5 billion guided last quarter.	1
29	**Non-interest revenue was up** $1.3 billion driven by **strong performance in the CIB**	1
30	Adjusted expense of $14.5 billion was up $500 million both year on year and quarter on quarter, largely driven by two notable expense items in Consumer which I'll talk about later as well as the increase in FDIC surcharge which took effect this quarter and some higher marketing expense.	0.77875733
31	Credit cost of $1.3 billion in the quarter includes Consumer reserve builds of $225 million primarily Card	-0.000193629
32	But against that we have a net reserve release in wholesale for Oil & Gas of about $50 million.	-0.001153902
33	So as I said net income was $6.3 billion	-0.000119323
34	And while down 8% year on year you will recall that there were a number of significant items in last year's results, most notably significant tax benefits	0.29547194
35	If you adjust for tax, legal expense and **credit reserves net income is up** over $800 million year on year.	0.99999905
36	Dealing with Oil & Gas here, we are encouraged by how quickly investor sentiment and risk appetite for the sector returned as the **outlook for both oil and gas prices continued to improve**	1

(b) Earnings Call with Max Sentiment

Figure 2: Earnings Calls for JPM with Minimum and Maximum Sentiment Scores

3 DATA AND EMPIRICAL DESIGN

3.1 Data

We consider as a baseline model a standard factor model for a representative sample of large and liquid stocks, in particular we consider the quarterly data over the sample $1980:01-2023:01$ of the 30 constituents of the Dow Jones Industrial Average index (DJIA) at the end of the sample, omitting from our analysis Dow Inc., which was included in the index only in 2019. This gives us an initial cross-section of 29 assets. The data on the Fama-French 5 factors [5] are retrieved from Ken French data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), where also data on the time-series of the riskfree rate are made available. Data on factor prices and asset prices are constructed by cumulating log(returns).

Our measure of sentiment is constructed by analyzing the text of quarterly earnings call, which we obtain via Refinitiv and Bloomberg. We analyze them using a FinBERT model. Earnings calls are conducted by companies with their board members, investors, analysts and the press. These calls typically occur once every quarter and are used to discuss the company's financial results and performance. Earnings calls serve as a platform for the company to communicate its financial performance and outlook to stakeholders. They also provide an opportunity for investors and analysts to ask questions and gain insights into the company's operations and prospects.

Earnings calls usually follow a structured format, consisting of two parts: the main presentation and a question-and-answer (Q&A) session. During the main presentation portion, the company's management, typically the CEO and CFO, provide a detailed overview of the financial results for the quarter or year. Management may also discuss strategic initiatives, market trends, and other factors that have influenced the company's performance. The main presentation is scripted and prepared in advance to ensure that important information is communicated clearly and accurately. A Q&A session follows the main presentation. In this session, analysts, investors, and the press have the opportunity to interact with the company's management. These questions can cover a wide range of topics, including specific financial results, future guidance, industry trends, and more. The Q&A session allows for direct engagement between the company and its stakeholders, providing additional insights beyond the prepared remarks.

Additionally, earnings calls can offer insights into the company's sentiment and risk perceptions. This information is derived through textual analysis of transcripts from these calls. Earnings calls are considered valuable because they provide timely information on a company's financial performance and offer insights into its management's perspective on the business. Furthermore, they are used to monitor sentiment and risk trends, which can offer valuable insights into the overall health of a company and its industry.

3.2 Building mis-pricing proxies

Several steps are necessary to build the cointegration-based mis-pricing proxies. First, asset prices and factor prices are constructed by cumulating (log) returns:

$$\ln P_{i,t} = \ln P_{i,t-1} + r_{i,t}, \tag{8}$$
$$\ln F_{i,t} = \ln F_{i,t-1} + f_{i,t} \tag{9}$$

Second, the long-run properties of the factor prices are investigated by checking the absence of any co-integrating relationship among them. If factor prices were to share some stochastic trends, then some of the factors would be redundant for pricing the assets. To test for no-cointegration among factor prices, we estimate the following VAR on them to apply the Johansen cointegration analysis [10]

$$\ln \mathbf{F}_t = A_0 + A_1 t + A_2(L) \ln \mathbf{F}_{t-1} + \mathbf{v}_t \ . \tag{10}$$
$$\ln \mathbf{F}_t = (lnF_{mkt,t} - lnF_{rf,t}, lnF_{smb,t}, lnF_{hml,t}, lnF_{rmw,t}, lnF_{cma,t})$$

Table 1 reports the empirical results and shows that the null of at most zero cointegrating vectors is not rejected at 1 percent critical level by the relevant test (the one for the specification that allows for the presence of a deterministic trend in the cointegrating vector).

Table 1: Cointegration Test on Factor Prices. This table reports the statistic and critical values for the Johansen maximum eigenvalue test on factor prices. The factor prices are obtained as the cumulative returns of a buy-and-hold strategy that invests in the 5 Fama French factors. r denotes the number of cointegrating relations. Quarterly data from $1980:Q1$ to $2023:Q1$.

	test	10pct	5pct	1 pct
$r \leq 4$	3.47	10.49	12.25	16.26
$r \leq 3$	5.09	16.85	18.96	23.65
$r \leq 2$	10.49	23.11	25.54	30.34
$r \leq 1$	18.11	29.12	31.46	36.65
$r = 0$	39.70	34.75	37.52	42.36

We then move to the cointegration analysis between asset prices and the factor prices. Again we apply the Johansen procedure that requires the specification of 29 VARs, on the vector of variables obtained by augmenting in turn the (log-)factor prices with the (log-)asset prices of the constituents of the DJIA at the end of the sample:

$$\ln \mathbf{Z}_t = A_0 + A_1 t + A_2(L) \ln \mathbf{Z}_{t-1} + \mathbf{v}_t, \tag{11}$$

$$\ln \mathbf{Z}_t = \big(\ln P_{i,t},\ \ln F_{mkt,t} - \ln F_{rf,t},\ \ln F_{smb,t},\ \ln F_{hml,t},\ \ln F_{rmw,t},\ \ln F_{cma,t}\big). \tag{12}$$

Table 2 reports the result of the Johansen analysis for the thirty constituent of the DJIA, showing that for 26 of the 29 assets the null of at most zero cointegrating vectors can be rejected at the 10pct critical level, if the 5pct critical value is adopted the number reduces to 16 assets, and if the strictest 1pct critical value is adopted then null is rejected only for 5 assets.

In the light of these mixed results on the capability of the Fama-French factor prices to capture the long-run trend in asset prices, we construct cointegration based mis-pricing proxies by considering only the 16 companies when the null of at most zero cointegrating vectors between factor prices and asset prices was rejected at the 5pct level and we drop from the analysis of returns those companies for which the null of no cointegrating vectors could not be rejected. Cointegration based mis-pricing proxies are then constructed as follows:

$$u^{CB}_{i,t} \equiv \ln P_{i,t} - \hat{\alpha}_{0,i} - \hat{\alpha}_{1,i} t - \hat{\beta}_i' \ln \mathbf{F}_t.$$

$$\begin{aligned}\ln \mathbf{F}_t = (&\ln P_{AXP,t}, \ln P_{BA,t}, \ln P_{CAT,t}, \ln P_{CRM,t},\\ &\ln P_{CSCO,t}, \ln P_{CVX,t}, \ln P_{DIS,t}, \ln P_{GS,t},\\ &\ln P_{HD,t}, \ln P_{JPM,t}, \ln P_{MRK,t}, \ln P_{MSFT,t},\\ &\ln P_{NKE,t}, \ln P_{UNH,t}, \ln P_{V,t}, \ln P_{WMT,t}).\end{aligned}$$

where the cointegrating parameters are estimated via static long-run regressions.[1]

Sentiment-based mispricing proxies for our selected assets are built using the detailed textual analysis approach described in the previus section. Specifically, we apply the FinBERT model to the same set of companies for which cointegration analysis between factor prices and stock prices has been implemented. We run FinBERT on the transcripts of earnings calls, where company leaders discuss their financial results and future plans. The model analyzes these transcripts to determine the sentiment of each report, assessing the overall tone and emotion expressed. This tone is computed as a weighted average of the sentiment of each sentence within the earnings calls. The sentiment score from each report provides us with a proxy for how the market might emotionally react to the information shared during the earnings call.

Table 2: Cointegration Test on Asset and Factor Prices. This table reports the statistic and critical values for the Johansen maximum eigenvalue test on asset and factor prices. Each row shows the test result considering the price of asset i and the price of the 5 Fama French factors. Each row shows tests for the null of at most zero cointegration relation among the series. The data is at the quarterly frequency, from $1980:Q1$ to $2023:Q1$ (unbalanced panel).

	test	10pct	5pct	1pct
AAPL	40.37	40.91	43.97	49.51
AMGN	43.01	40.91	43.97	49.51
AXP	47.36	40.91	43.97	49.51
BA	50.29	40.91	43.97	49.51
CAT	46.54	40.91	43.97	49.51
CRM	62.65	40.91	43.97	49.51
CSCO	59.13	40.91	43.97	49.51
CVX	49.65	40.91	43.97	49.51
DIS	46.82	40.91	43.97	49.51
GS	47.54	40.91	43.97	49.51
HD	45.33	40.91	43.97	49.51
HON	42.92	40.91	43.97	49.51
IBM	41.73	40.91	43.97	49.51
INTC	40.25	40.91	43.97	49.51
JNJ	41.02	40.91	43.97	49.51
JPM	48.21	40.91	43.97	49.51
KO	49.30	40.91	43.97	49.51
MCD	42.75	40.91	43.97	49.51
MMM	43.93	40.91	43.97	49.51
MRK	47.89	40.91	43.97	49.51
MSFT	44.99	40.91	43.97	49.51
NKE	49.13	40.91	43.97	49.51
PG	41.14	40.91	43.97	49.51
TRV	41.33	40.91	43.97	49.51
UNH	47.77	40.91	43.97	49.51
V	66.29	40.91	43.97	49.51
VZ	40.08	40.91	43.97	49.51
WBA	42.74	40.91	43.97	49.51
WMT	48.75	40.91	43.97	49.51

[1]Robustness of these estimates to the omission of the short-term dynamics has been checked via the ARDL approach, which gives negligible differences in the mispricing proxies

3.3 Mis-pricing proxies in the FF factor model

On the basis of the evidence of low correlation between the two mispricing measures we investigate their importance in FF factor model by estimating first a standard factor model for the 16 companies selected in the previous section:

$$r_{i,t+1} = \alpha_i + \boldsymbol{\beta}_i' \boldsymbol{f}_{t+1} + \epsilon_{i,t+1}, \tag{13}$$

and then by augmenting the standard factor model with the two proposed mispricing proxies to estimate the following system of equations

$$r_{i,t+1} = \alpha_i + \boldsymbol{\beta}_i' \boldsymbol{f}_{t+1} + \delta_i^{CB} u_{i,t}^{CB} + \delta_i^{SB} u_{i,t+1}^{SB} + \epsilon_{i,t+1}, \tag{14}$$

Table 3 reports the results of augmenting the standard FF model with the Cointegration based and the Sentiment based mispricing proxies. Two versions of model (14) have been estimated: in the first version the speed of adjustment with respect to disequilibrium is allowed to be heterogenous across assets, while in the second version is restricted to be the same. In the first version of the model the inclusion of the mispricing proxies leaves estimated coefficients on factors substantially unaltered with respect to those obtained in the standard Fama-French specification, but both mispricing proxies carry some additional predictability. The coefficients on $u_{i,t}^{CB}$ are significant for 12 tickers, with a very similar magnitude. When the same speed of adjustment is imposed on all tickers, the estimated coefficient takes a value of -0.109 significant at the 1 per cent level, implying that about one-tenth of the mispricing is corrected over the one-quarter horizon. This evidence of a strongly significant partial adjustment coefficient estimated with panel restriction is consistent with the results in the recent literature estimating the impact of relative leverage in corporate finance [9]. The coefficients on $u_{i,t}^{SB}$ are significant for 7 tickers, with a very similar magnitude. When the homogeneity restriction is imposed on all tickers, the estimated coefficient takes a value of 0.105 significnt at the 1 per cent level, implying that the returns are positively affected by sentiment after controlling for common factors and idiosyncratic fluctuations driven by the cointegration based-mispricing proxy.

Table 3: Fama–French Five-Factor Model with CB and SB Mispricing Proxies. This table reports the coefficient estimates for the estimation of system (14). Sample of quarterly data 2001:1-2023:1, number of observations not balanced across equations. Standard errors are shown in parentheses.

	Dependent variable: $r_{i,t+1}$							
	Intercept	exmkt	smb	hml	rmw	cma	$u^{CB}_{i,t}$	$u^{SB}_{i,t+1}$
AXP	0.004	1.363***	-0.473*	0.908***	-0.662**	-0.532	-0.156**	-0.069
	(0.009)	(0.12)	(0.261)	(0.214)	(0.257)	(0.337)	(0.068)	(0.063)
BA	-0.006	1.302***	0.298	0.611*	0.105	-0.304	-0.122*	0.217*
	(0.016)	(0.195)	(0.439)	(0.363)	(0.421)	(0.549)	(0.07)	(0.122)
CAT	0.01	1.142***	0.474	0.07	0.076	0.872**	-0.187***	0.144**
	(0.012)	(0.157)	(0.329)	(0.264)	(0.325)	(0.412)	(0.064)	(0.065)
CRM	0.031**	1.118***	-0.085	-0.678**	-0.507	-0.38	-0.241***	0.322
	(0.014)	(0.179)	(0.378)	(0.311)	(0.398)	(0.52)	(0.067)	(0.202)
CSCO	0.004	1.095***	-0.199	0.068	-0.492	0.368	-0.079**	0.024
	(0.012)	(0.141)	(0.303)	(0.255)	(0.304)	(0.394)	(0.031)	(0.122)
CVX	0.003	0.796***	0.193	0.257	0.629**	0.675*	-0.073	0.165*
	(0.011)	(0.149)	(0.31)	(0.251)	(0.314)	(0.385)	(0.061)	(0.096)
DIS	0.001	1.083***	0.223	0.33	-0.366	-0.449	-0.023	0.081
	(0.01)	(0.131)	(0.28)	(0.225)	(0.28)	(0.345)	(0.039)	(0.074)
GS	-0.009	1.259***	0.048	0.896***	-0.15	-0.66*	-0.184***	0.135*
	(0.012)	(0.148)	(0.313)	(0.255)	(0.313)	(0.392)	(0.068)	(0.068)
HD	0.003	0.983***	-0.061	-0.177	0.307	0.525	-0.034	-0.004
	(0.012)	(0.151)	(0.338)	(0.257)	(0.323)	(0.393)	(0.061)	(0.091)
JPM	0.011	1.075***	0.13	0.89***	-0.884***	-0.037	-0.168**	0.101*
	(0.01)	(0.128)	(0.284)	(0.228)	(0.261)	(0.328)	(0.073)	(0.059)
MRK	-0.004	0.695***	-0.499	-0.475**	-0.077	1.047***	-0.227***	0.123
	(0.011)	(0.135)	(0.333)	(0.228)	(0.277)	(0.352)	(0.069)	(0.086)
MSFT	0.012	1.152***	-0.576**	-0.06	-0.055	-0.425	-0.093**	0.095
	(0.009)	(0.117)	(0.251)	(0.202)	(0.243)	(0.298)	(0.039)	(0.074)
NKE	0.013	1.003***	-0.305	0.003	0.321	-0.016	-0.193**	0.438***
	(0.013)	(0.163)	(0.334)	(0.277)	(0.37)	(0.459)	(0.081)	(0.162)
UNH	0.002	0.775***	0.237	-0.147	0.551*	0.372	-0.14***	0.225**
	(0.012)	(0.125)	(0.293)	(0.234)	(0.276)	(0.365)	(0.045)	(0.092)
V	0.022*	0.894***	-0.45	-0.269	-0.329	0.304	-0.22*	-0.087
	(0.012)	(0.13)	(0.294)	(0.246)	(0.352)	(0.401)	(0.114)	(0.113)
$\delta^{CB}_i = \delta^{CB}$, $\delta^{SB}_i = \delta^{SB}$							−0.109***	0.105***
							(0.014)	(0.021)
Note:								*p<0.1; **p<0.05; ***p<0.01

3.4 Sentiment-dependent nonlinear adjustment

We therefore allow the ECT response to differ between overpricing and underpricing and to vary with sentiment. Define $u^{CB,+}_{i,t} = u^{CB}_{i,t}$ when $u^{CB}_{i,t} > 0$ and zero otherwise, and define $u^{CB,-}_{i,t}$ analogously for negative deviations. We estimate

$$\begin{aligned} r_{i,t+1} = {} & \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_{t+1} + \delta^{SB}_0 u^{SB}_{i,t+1} \\ & + \left(\delta^{CB,+}_0 + \delta^{CB,+}_1 u^{SB}_{i,t}\right) u^{CB,+}_{i,t} \\ & + \left(\delta^{CB,-}_0 + \delta^{CB,-}_1 u^{SB}_{i,t}\right) u^{CB,-}_{i,t} + \epsilon_{i,t+1}. \end{aligned} \tag{15}$$

Table 4 summarizes the estimates. When prices are below their

Table 4: Mispricing proxies and adjustment speed

Specification	Coefficient	Std. error
Linear: δ^{CB}	-0.109^{***}	0.014
Linear: δ^{SB}	0.105^{***}	0.021
Nonlinear: δ_0^{SB}	0.067^{*}	0.035
Nonlinear: $\delta_0^{CB,+}$	-0.087^{***}	0.026
Nonlinear: $\delta_1^{CB,+}$	0.444^{***}	0.177
Nonlinear: $\delta_0^{CB,-}$	-0.127^{***}	0.027
Nonlinear: $\delta_1^{CB,-}$	-0.012	0.193

$^{***}p < 0.01$, $^{*}p < 0.10$.

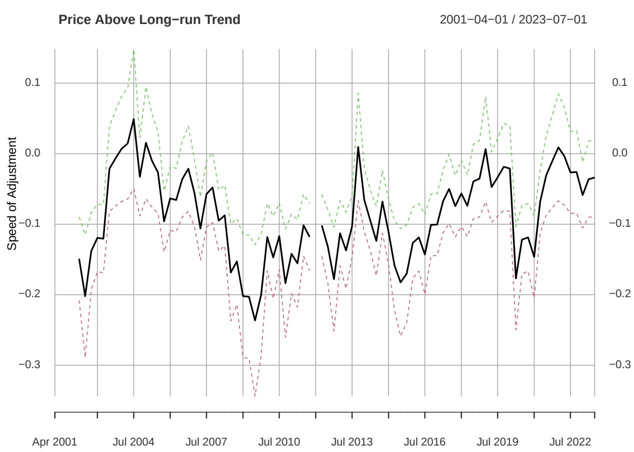

Figure 3: Sentiment-dependent adjustment for American Express when price is above its factor-implied trend. Dotted lines denote 90% confidence intervals.

long-run trend, the adjustment coefficient is negative and stable: $\widehat{\delta}_0^{CB,-} = -0.127$, while its interaction with sentiment is economically small and insignificant. When prices are above trend, the baseline adjustment remains negative, $\widehat{\delta}_0^{CB,+} = -0.087$, but the interaction with sentiment is positive and significant, $\widehat{\delta}_1^{CB,+} = 0.444$. Hence favorable sentiment makes the adjustment coefficient less negative and slows convergence. At sufficiently high sentiment, correction can temporarily cease or reverse.

The direct sentiment coefficient falls from 0.105 in the linear model to 0.067 and is significant only at the 10% level. Thus, much of sentiment's incremental predictive content is explained by its effect on the persistence of overpricing rather than by an additive return channel. The asymmetry is consistent with limits to arbitrage: correcting overvaluation often requires short selling, while undervaluation can be traded through ordinary purchases. It is also consistent with diagnostic expectations, because favorable corporate communication can validate beliefs that support an elevated valuation.

Figure 3 illustrates the mechanism for American Express. The adjustment speed varies with call sentiment when the ECT is positive and is occasionally close to or above zero. Corresponding plots for negative deviations and other diagnostics are provided in the Web Appendix.

4 CONCLUSION

Stock-specific deviations from factor-implied price trends and earnings-call sentiment both add predictive content to the Fama–French five-factor model. Their joint role is parsimoniously captured by a nonlinear equilibrium-correction model. Prices below trend revert at a relatively stable rate; prices above trend revert more slowly when sentiment is favorable. Once this interaction is included, the direct sentiment effect becomes substantially weaker.

The results connect textual information to the dynamics of factor-model mispricing. They also suggest practical applications: monitoring the ECT together with earnings-call sentiment may improve conditional return forecasts, risk measurement, and portfolio decisions. Future work can evaluate the mechanism in broader equity universes and in real-time forecasting designs.

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