Journal of Financial Economics 162 (2024) 103952

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/finec

Macroeconomic perceptions, financial constraints, and anomalies[☆]

Wei He[a], Zhiwei Su[b,*], Jianfeng Yu[c,d]

[a] Institute of Chinese Financial Studies, Southwestern University of Finance and Economics, Chengdu, China
[b] Faculty of Business, Lingnan University, Hong Kong, China
[c] PBC School of Finance, Tsinghua University, Beijing, China
[d] Hong Kong University of Science and Technology, Hong Kong, China

ARTICLE INFO

Dataset link: Replication Package (Original data)

JEL classification:
E70
E71
G12
G41

Keywords:
Anomalies
Financial constraints
Overreaction
Subjective expectations

ABSTRACT

This paper studies the heterogeneous effects of subjective macroeconomic expectations on the cross-section of equity returns. We argue that an upward revision in expectations of macroeconomic productivity might be accompanied by an excessive increase in investment and external financing, inflated current equity prices, and thus lowered subsequent returns, particularly for financially constrained firms. Thus, following upward revisions in expectations of macroeconomic productivity, subsequent returns are relatively low for small firms, value firms, low-investment firms, risky firms, unprofitable firms, low-quality firms, and financially distressed firms—all of which are more financially constrained. In sharp contrast, following downward revisions in expectations of macroeconomic productivity, these categories of firms earn relatively high subsequent returns. We find that revisions in subjective macroeconomic expectations induce strong predictable time variation in a large set of anomalies. In particular, favorable revisions in expectations of macroeconomic productivity predict significantly stronger profitability, quality, distress, and low-risk anomalies but weaker value, investment, and size anomalies.

1. Introduction

The idea that real macroeconomic fundamentals drive anomaly returns is theoretically grounded but empirically inconclusive (e.g., Cochrane, 2017 and Lochstoer and Tetlock, 2020). However, recent evidence shows that subjective expectations are more effective than realized outcomes in explaining market returns (De la and Myers, 2021) and real corporate activities (e.g., Gennaioli et al., 2016 and Gulen et al., 2023). Thus, a natural question to ask is whether subjective macroeconomic expectations would be helpful in explaining the time variation in anomaly returns.

More specifically, recent studies document that both investors and firm managers tend to extrapolate economic fundamentals and stock returns, becoming overoptimistic after good news and overpessimistic after bad news. For example, Bordalo et al. (2019), Bordalo et al. (2021), and Deng (2023) show that revisions in analysts' and managers' earnings growth forecasts negatively predict their forecast errors, consistent with extrapolative expectations. Moreover, subjective expectations can affect firm behaviors such as investments and external financing. Overoptimistic earnings growth expectations lead to more investment, more external financing, and lower credit spreads in the short run, but reversals in the longer run (Gennaioli et al., 2016; Bordalo et al., 2021; Deng, 2023).

In this paper, motivated by the evidence of biased firm earnings growth expectations influencing firm-level investment and external financing, we study the effect of perceptions of macroeconomic conditions on the cross-section of stock returns, partly through their differential effects on firms with different characteristics.[1] We find that macroeconomic productivity perception is a key driver of the time variation in a broad set of prominent asset pricing anomalies. The question of what drives the time-series variation in anomaly returns has been the focus of recent asset pricing studies. The answer to this question can not only help differentiate alternative interpretations of

☆ Nikolai Roussanov was the editor for this article. We thank the editor and two referees for their comments. We are also grateful for comments from Hengjie Ai, Zhiyao Chen, Yao Deng, Winston Wei Dou, Honglin Ren, Zhan Shi, Quan Wen, and seminar participants at the 2022 China International Conference in Finance, and the 2024 Asian Finance Association Annual Conference. J. Yu acknowledges financial support from the National Natural Science Foundation of China [Grants 72141304 and 72342020].

* Corresponding author.
E-mail addresses: wei_he@swufe.edu.cn (W. He), zhiweisu@ln.edu.hk (Z. Su), yujf@pbcsf.tsinghua.edu.cn (J. Yu).

[1] We use the terms macroeconomic conditions and aggregate productivity interchangeably.

https://doi.org/10.1016/j.jfineco.2024.103952
Received 26 December 2022; Received in revised form 29 September 2024; Accepted 29 September 2024
Available online 5 October 2024

the anomalies[2] but also provide additional stylized facts to discipline new theoretical models. In addition, it contributes to the advancement of factor investing in practice.

To see why macroeconomic productivity perceptions drive anomaly returns, we hypothesize that their effects are heterogeneous across firms. For example, an upward revision in expectations of aggregate productivity could stimulate optimism among both firm managers and investors, and thus coincide with an increase in external financing and investment, a decrease in financing costs, an increase in contemporaneous equity prices, and a lowered subsequent return. We hypothesize that such effect could be stronger for financially constrained firms. Indeed, Baker et al. (2003), Warusawitharana and Whited (2016), and Deng (2023) find that activities of financially constrained firms are more affected by misvaluation shocks or behavioral biases such as extrapolation and overoptimism. Thus, accompanying an upward revision in expectations of aggregate productivity, financially constrained firms could issue a lot of potentially low-quality debt and overinvest; later they would suffer from these inefficient investments and debt issuance, leading to lower subsequent returns. This is an inefficient investment channel. In addition, it is possible that, accompanying an upward revision in expectations of aggregate productivity, investors become overoptimistic about the future fundamentals such as earnings growth of financially constrained firms, probably because they believe that better macro conditions can alleviate frictions for these firms. Meanwhile, managers could issue overpriced equity and debt to exploit investor optimism. This market timing channel also implies subsequent return reversals for financially constrained firms. In Section 4, we provide detailed discussions of corporate activities and their alternative interpretations.

Overall, our argument suggests that the small, unprofitable, risky, distressed firms, as well as firms with analogous characteristics, are likely to be more affected by macroeconomic misperceptions. Indeed, according to Whited and Wu (2006), Hadlock and Pierce (2010), and Kaplan and Zingales (1997), these firms tend to face greater financial constraints. More recently, Lian and Ma (2021) document that for US nonfinancial firms, 80% of corporate debt represents cash-flow-based lending, which depends on firms' operating profitability, and 20% of the debt represents asset-based lending, which is tied to the pledgeability of physical assets. Thus, unprofitable firms would be more financially constrained than profitable firms because the prevalent lending practices restrict total debt as a multiple of operating earnings. On the other hand, value firms and low-investment firms would also be more financially constrained than growth firms and high-investment firms, given that their low-equity valuations and low investment are typically a result of poor cash flow (Maio, 2014; Lian and Ma, 2021).[3] Taken together, the various parts of our argument imply that macroeconomic perceptions should induce strong time variations in anomalies based on profitability, quality, financial distress, volatility, book-to-market, investment, and size since the long and short legs of these anomalies have different degrees of financial constraints.

Consistent with this prediction, we find that following upward revisions in expectations of macroeconomic conditions, subsequent equity returns are relatively low for small, risky, unprofitable, low-quality, and financially distressed firms. On the other hand, following downward revisions in expectations of macroeconomic conditions, these categories of firms earn relatively high subsequent returns. Thus, revisions in expectations of macroeconomic conditions induce strong predictable time variations in anomalies based on these characteristics. In particular, favorable revisions in expectations of aggregate productivity predict stronger profitability, quality, and low-risk anomalies but weaker value, investment, and size anomalies.

More precisely, using revisions in expectations of one-quarter-ahead industrial production growth (IPG) from the Survey of Professional Forecasters (SPF), we quantify changes in investors' perceptions of aggregate productivity. Therefore, upward revisions in IPG expectations indicate that investors now expect higher industrial production growth than they did in the previous quarter. Empirically, we find that these revisions strongly affect asset pricing anomalies. The average return spread of profitability, quality, distress, and low-risk anomalies is 3.73% per quarter following upward revisions in IPG expectations and –0.35% per quarter following downward revisions. In contrast, IPG forecast revisions show the opposite predictive power for value, investment, and size anomalies. The average return spread of value, investment, and size anomalies is –1.30% per quarter following upward revisions in IPG expectations and 2.34% per quarter following downward revisions.

Notice that it is well known from Coibion and Gorodnichenko (2015) that consensus forecasts tend to be sticky and may seem to underreact. However, our argument above suggests that investors overreact to IPG forecast revisions. In Section 4.6, we will reconcile this apparent discrepancy in more detail. Here, we outline the key argument. The existing literature (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Afrouzi et al., 2023) suggests that the positive correlation between (ex ante) forecast revisions and (ex post) forecast errors at the consensus level results from information rigidities and the aggregation of individual forecasts, rather than a behavioral bias-induced underreaction. While consensus macro forecasts themselves typically display stickiness (Bordalo et al., 2020), investors and managers may still overreact to the SPF forecast revisions. For example, investors may use SPF consensus forecasts as public signals alongside their private signals. When self-attribution and overconfidence biases are large enough, investors could appear to overreact to the public signal, even if the public signal itself has an apparent sticky feature. We formalize this argument with a simple model in the Appendix.

Since our results indicate that following upward revisions, some anomalies are more pronounced while others are weaker, we can construct a refined portfolio strategy based on strategy rotation. Specifically, the rotation strategy invests in profitability, quality, distress, and low-risk anomalies following upward IPG forecast revisions, and invests in value, investment, and size anomalies otherwise. We find that the Sharpe ratio of this rotation strategy is 0.71 per annum, significantly higher than those of individual factor strategies, which are 0.29 for profitability, quality, distress, and low-risk anomalies and 0.22 for value, investment, and size anomalies. This rotation strategy even earns a significant Fama and French (2015) five-factor alpha of 1.93% per quarter, although underlying anomalies generally do not.

Our documented time variation in anomaly returns could also result from rational reasons, including innovations in either risk aversion or the amount of risks, as opposed to our proposed behavioral forces. To further distinguish between the behavioral and rational interpretations, we perform several additional tests. First, we inspect the subsequent earnings forecast errors for anomaly portfolios following both upward and downward revisions in IPG expectations. We find predictable patterns in forecast errors consistent with our behavioral interpretation. For example, the difference in long-term earnings growth forecast errors (realized minus forecasts) between profitable firms and unprofitable firms tends to be greater after upward revisions in IPG expectations than after downward revisions. Conversely, forecast error differences between value firms and growth firms tend to be lower

[2] Economists sharply disagree about the sources of the anomaly returns and propose both risk-based and behavioral theories as explanations. Anomaly premia could vary over time because of time variation in (i) the degree of risk aversion (Campbell and Cochrane, 1999), (ii) the amount of risk (Bansal and Yaron, 2004; Gabaix, 2008), (iii) investor sentiment (Baker and Wurgler, 2006; Stambaugh et al., 2012), (iv) the degree of bias in expectations (Cassella and Gulen, 2018; He et al., 2023), and other factors.

[3] Fama and French (1995) show that value firms tend to have more persistent lower earnings, and hence are more financially constrained, than growth firms. Similarly, the results of Cooper et al. (2008) suggest that low-investment firms tend to be small, unprofitable, and have high book-to-market ratios, making them more financially constrained.

after upward revisions than after downward revisions. Second, we run horse races with other economic variables that comove with business cycles, such as the surplus consumption ratio (a proxy for effective risk aversion). We find that surplus consumption ratio either cannot significantly predict anomaly returns or predicts with an incorrect sign. Lastly, we also control for other well-known anomaly predictors such as investor sentiment, degree of extrapolative weighting, return dispersion, value spread, and anomaly return volatilities. We verify that the predictive power of macroeconomic perceptions remains almost unchanged after controlling for these variables.

To further support our hypothesized mechanism for the time variation in anomalies, we inspect the behaviors of firms in the anomaly portfolios during upward and downward IPG forecast revisions. We find that in tandem with an upward revision in IPG expectations, investors become overoptimistic about long-term fundamentals, particularly for the financially constrained firms. The constrained firms experience a greater increase in their external financing and investment, as well as a larger reduction in the credit spread and the degree of financial constraint. In addition, we follow Richardson (2006) and measure overinvestment as the residual of regressing investment on a set of firm characteristics to filter out firms' growth opportunities. The empirical evidence suggests that financially constrained firms overinvest (underinvest) during upward (downward) IPG forecast revisions. We also examine the market timing interpretation, which suggests that managers of financially constrained firms respond to upward IPG forecast revisions by issuing overpriced equity and low-quality bonds. Overall, we find evidence, albeit somewhat weak, for both the overinvestment and market timing channels.

These findings accord with the theoretical mechanisms in Bordalo et al. (2021), Deng (2023), and Gulen et al. (2023), who focus on how misperceptions of firm earnings growth affect corporate activities, whereas we focus on how macroeconomic productivity perceptions predict anomaly returns. Their models provide the closest theoretical framework for our empirical analysis. Gulen et al. (2023) imply that firms facing more financial frictions should experience larger fluctuations in response to shocks in perceived credit market sentiment. Additionally, Deng (2023) shows that the interaction between financial frictions and extrapolative expectations results in stronger responses to productivity shocks among financially constrained firms as the feedback from the financial market affects investment and financing decisions through the cost of capital. We will discuss these mechanisms in greater detail in Section 4.

Moreover, we study the return predictability for portfolios directly sorted on financial constraint indices proposed by the literature and find consistent evidence. In particular, we use three different proxies for financial constraints, as in Whited and Wu (2006), Hadlock and Pierce (2010), and Kaplan and Zingales (1997). Despite the debate over whether they earn positive average returns, portfolios that long constrained firms and short unconstrained firms based on three different financial constraint indices all deliver negative (positive) returns following upward (downward) revisions in IPG expectations. We find that the portfolios that long constrained firms and short unconstrained firms earn 3.41% higher returns per quarter (t-statistic = 3.67) following downward IPG forecast revisions compared to upward revisions, despite earning close to zero returns on average in the sample period.

The paper also helps explain the negative correlation between the profitability premium and the value premium, as emphasized in Novy-Marx (2013). The investment and operating cash flows of profitable firms resemble growth firms, whereas those of unprofitable firms resemble value firms (Kogan et al., 2023; Dou et al., 2022). However, the standard production-based asset pricing models imply positive comovement between these two anomalies (Ai et al., 2021). On the other hand, the negative correlation between the profitability premium and the value premium is natural based on our argument since both unprofitable (the short leg of the profitability anomaly) and value firms (the long leg of the value anomaly) are more financially constrained and more influenced by macroeconomic perceptions.[4] Thus, this paper offers a potential mechanism to account for this negative correlation by highlighting the interaction between macroeconomic (mis)perceptions and financial constraints as a key driver of asset returns.

Lastly, we also provide comprehensive robustness checks in the following ways. First, we verify that our results remain valid when using forecast revisions of longer horizons, alternative macroeconomic productivity measures, and surveys that poll different market participants. Second, we show that our results are not driven by risk-based explanations such as effective risk aversion, market risk, macroeconomic risk, and macroeconomic uncertainty. Third, we run horse races between forecast revisions and realized shocks and show that subjective expectations dominate realized macroeconomic variables in predicting anomalies.

Our study is related to several strands of research in macroeconomics and asset pricing. First, the paper contributes to the burgeoning work studying how extrapolation bias—more generally, misperception—affects asset prices, firm real activities, and macroeconomic outcomes. Bordalo et al. (2018), Gulen et al. (2023), and Greenwood et al. (2021) examine how investors' misperceptions explain aggregate credit cycles. There is also an emerging literature on expectations of firm fundamentals influencing firm activities such as investment and external financing, as well as credit spreads and aggregate credit cycles (Bordalo et al., 2021; Gulen et al., 2023). Barberis et al. (2015, 2018), Cassella and Gulen (2018), and Jin and Sui (2022) examine how extrapolation leads to asset bubbles, reversals, and a large equity premium. We add to this literature by emphasizing the interaction between the extrapolation bias and firm financial constraints in influencing asset prices, a topic largely unexplored by previous studies, with few exceptions. In particular, Gulen et al. (2023) and Deng (2023) also find that financial constraints can amplify the mispricing caused by credit sentiment or extrapolation. We differ by examining the interaction effect of macroeconomic perceptions and firm-level financing constraints on the time-variation in a broad set of anomalies.

Second, this study is also related to the vast literature on anomaly timing. Existing studies have proposed different economic drivers for different anomalies. In this paper, we suggest that macroeconomic perceptions drive a large set of well-known anomalies simultaneously through their differential impact on financially constrained legs. Relatedly, Birru (2018) finds that anomalies with speculative long legs perform better on Fridays, and anomalies with speculative short legs perform better on Mondays, as mood tends to increase from Thursday to Friday and decrease on Monday. Previous studies have documented several other anomaly predictors. In particular, investor sentiment and anomaly return volatility are prominent predictors (see, e.g., Baker and Wurgler, 2006, Stambaugh et al., 2012, Antoniou et al., 2013, and Moreira and Muir, 2017). It is noteworthy that revisions in expectations of aggregate productivity differ from investor sentiment in two important dimensions. First, revisions in expectations of aggregate productivity have clear counterparts in structural models, affecting real corporate activities including financing and investment. However, investor sentiment is an elusive concept of investor misperception (Baker and Wurgler, 2006). Second, they have distinct empirical implications for predictability. IPG forecast revisions yield opposite predictive power for different sets of anomalies (stronger profitability, quality, distress, and low-risk anomalies but weaker value, investment, and size anomalies), whereas investor sentiment typically predicts a host of anomalies with the same positive sign, as argued by Stambaugh et al. (2012). Moreover, our results are robust after controlling for many existing anomaly predictors. We advance this strand of literature by not only providing a robust anomaly predictor but also identifying potential underlying mechanisms.

[4] Kogan et al. (2023) and Dou et al. (2022) can also account for this negative correlation under a rational framework.

Finally, this paper is also related to the work on the nexus between macroeconomics and finance. López-Salido et al. (2017) document that the investment and debt issuance of firms with lower credit ratings are more sensitive to credit conditions. Campello and Chen (2010) and Maio (2014) show that macroeconomic movements and monetary policy actions have a greater impact on the contemporaneous fundamentals and returns of financially constrained firms. In addition, many existing studies find a weak connection between realized macroeconomic variables and asset prices (see, e.g., Chen et al., 1986, Shanken and Mark, 2006, Shen et al., 2017, Herskovic et al., 2019, Lochstoer and Tetlock, 2020, and Giglio et al., 2021). Different from these papers, we suggest that the interaction between (forward-looking) macroeconomic perceptions and financial constraints can generate cross-sectional differences in both corporate activities and expected stock returns, inducing significant time variation in anomaly returns. Our study highlights the importance of forward-looking macroeconomic perceptions, rather than realized macroeconomic quantities, in influencing asset prices.

The remainder of this paper is organized as follows. Section 2 presents the data and summary statistics. Section 3 provides the empirical results on the predictive power of macroeconomic productivity perceptions. Section 4 explores the economic mechanism. Finally, Section 5 concludes.

2. Data description and summary statistics

This section first describes the construction of the main variables used in the study and then provides descriptive statistics for the variables.

2.1. Data sources

Our data come from several sources. We obtain accounting information from Compustat, stock returns from CRSP, firm-level earnings growth forecasts from I/B/E/S, and corporate bond yield from the Trade Reporting and Compliance Engine (TRACE). We include domestic common shares trading on NYSE, Amex, and Nasdaq and exclude firms with primary standard industrial classifications between 4900 and 4999 (utilities) and between 6000 and 6999 (financials) and firms with negative book equity. Stock returns are corrected for the delisting bias. The risk-free rate is proxied as the one-month Treasury bill rate taken from Kenneth French's data library. Finally, we collect forecasts of aggregate productivity from the SPF database, which is currently maintained by the Federal Reserve Bank of Philadelphia. Unless otherwise noted, the full sample starts from 1969Q1, when data on forecast revisions become available, and ends in 2019Q4.

2.2. Stock market anomalies

To test our intuition outlined in the introduction, we construct a set of anomalies. We apply two criteria in selecting anomalies to ensure that the selection is both parsimonious and economically meaningful. First, existing studies show that the firms in the short and long legs of the anomaly face different financial constraints. Second, the anomalies are either related to the underlying characteristics of some factors in prominent factor models since these factors can account for a large set of other anomalies, or related to the low-risk anomaly since it runs counter to the fundamental principle in finance that higher risk is compensated with a higher expected return (e.g., Baker et al., 2011). As a result, we choose size, book-to-market, asset growth, return on assets, return on equity, and operating profits as they are related to the factors of Fama and French (2015) and Hou et al. (2015). We also include anomalies based on total volatility, idiosyncratic volatility, failure probability, and O-score since these anomalies violate the fundamental principle of risk–return tradeoff. We further add the quality anomaly of Asness et al. (2019) and the long-term reversals of De Bondt and Thaler (1985) since their underlying characteristics are related to those of the profitability factor and book-to-market factor, respectively. In addition, the quality factor itself (Asness et al., 2019) can explain many other anomalies. Overall, these 12 anomalies are well-documented in the literature and are potentially related to biased beliefs and financial constraints.[5] Table 1 lists the 12 anomalies, along with the ex ante evidence that links these anomalies to biased beliefs and financial constraints.

The anomalies in Table 1 Panel A have more financially constrained short legs. Historically, profitable firms deliver higher average returns than unprofitable firms, high-quality firms and non-distressed firms deliver higher average returns than low-quality firms and distressed firms, and low-risk firms deliver higher average returns than high-risk firms. We study the following profitability, quality, distress, and low-risk category anomalies: (1) return on assets (ROA), calculated as income before extraordinary items divided by total assets following Hou et al. (2015); (2) return on equity (ROE), calculated as income before extraordinary items divided by total book equity following Hou et al. (2015); (3) operating profitability (OP), calculated as the ratio of a firm's operating profits to its assets following Fama and French (2015) and Hou et al. (2015); (4) quality score (Quality), calculated as the z-score combination of profitability, growth, and safety components following Asness et al. (2019); (5) failure probability (FProb), calculated as the predicted probability of bankruptcy from a dynamic logit model following Campbell et al. (2008); (6) Ohlson's O-score (O-Score) as based on several financial ratios to estimate the probability of bankruptcy (Ohlson, 1980); (7) total volatility (TV), calculated as the standard deviation of a stock's daily returns in the prior month following Hou et al. (2015); and (8) idiosyncratic volatility (IVOL), calculated as the standard deviation of the residuals from the Fama and French (1993) three-factor model using daily excess returns in the prior month following Ang et al. (2006).

Table 1 Panel B lists anomalies with more financially constrained long legs: value firms earn higher average returns than growth firms, low-investment firms earn higher average returns than high-investment firms, and small firms earn higher average returns than large firms. Specifically, we study the following value, investment, and size category anomalies: (1) book-to-market equity (BM), calculated as book equity divided by market equity following Fama and French (1992); (2) long-term reversals (LTR), calculated as prior returns from month $\tau-60$ to $\tau-13$ following De Bondt and Thaler (1985); (3) investment-to-assets (IA), calculated as the growth rate of total assets following Cooper et al. (2008); and (4) market capitalization (SIZE), calculated as price times shares outstanding following Banz (1981) and Fama and French (1993).[6]

To control for the effect of microcaps, we form decile portfolios using NYSE breakpoints and calculate value-weighted returns for each decile. The deciles for Quality, FProb, TV, IVOL, and LTR are rebalanced monthly, and the others are rebalanced annually. The strategy return is then computed as the difference between the returns on the long and short portfolios (the two extreme deciles) following the

[5] We acknowledge that we might miss some other anomalies that also satisfy our two criteria. Thus, to alleviate data snooping concerns, we show in Section 4.4 that a similar conclusion is reached when repeating the analysis for long-short portfolios sorted directly on firm-level financial constraint indices.

[6] We do not include valuation anomalies based on operational activities such as cash flow-to-price (CP), dividend yield (DP), and earnings-to-price (EP) because these sorting characteristics have unclear links to financial constraints. On the one hand, firms with high CP, DP, and EP are value firms, and their low valuation could be due to poor fundamentals (similar to Tobin's q in the WW index), thus making them more financially constrained. On the other hand, firms with high CP, DP, and EP could mechanically have higher cash flow, dividend payout, and earnings, thus making them less financially constrained. Indeed, in unreported analysis, we find that the difference in the financial constraint index between high- and low-EP/CP/DP firms is statistically insignificant.

Table 1
Stock market anomalies.
The table displays the 12 prominent anomalies that this paper tries to link to biased beliefs and financial constraints. The second column lists the acronyms that are used in subsequent tables to refer to the anomalies. The third column lists the literature that attributes the anomaly to biased beliefs. The fourth column lists the literature that links the anomaly characteristic to financial constraints or their major components (size, age, and profitability).

Anomaly	Acronym	Evid. of biased beliefs	Evid. of financial constraints
		Panel A: Short leg more financially constrained	
Return on assets	ROA	Stambaugh et al. (2012)	Lian and Ma (2021)
Return on equity	ROE	Chen et al. (2023)	Lian and Ma (2021)
Operating profitability	OP	Chen et al. (2023)	Lian and Ma (2021) and Whited and Wu (2006)
Quality	Quality	Asness et al. (2019)	Based on profitability, profitability growth, and safety
Failure probability	FProb	Stambaugh et al. (2012)	Hoberg and Maksimovic (2015)
Ohlson's O-score	O-Score	Stambaugh et al. (2012)	Hoberg and Maksimovic (2015)
Total volatility	TV	Pflueger et al. (2020)	Dasgupta et al. (2011) and Lin and Paravisini (2013)
Idiosyncratic volatility	IVOL	Hou and Loh (2016) and Stambaugh et al. (2015)	Jiang et al. (2009)
		Panel B: Long leg more financially constrained	
Book-to-market equity	BM	Lakonishok et al. (1994)	Fama and French (1995) and Maio (2014)
Long-term reversals	LTR	De Bondt and Thaler (1985)	Lamont et al. (2001) and Maio (2014)
Asset growth	IA	Cooper et al. (2008)	Cooper et al. (2008)
Market capitalization	SIZE	Barberis et al. (2021)	Hadlock and Pierce (2010)

Table 2
Summary statistics for the anomalies.
The table reports summary statistics for the anomalies with more financially constrained short legs (long legs) in Panel A (Panel B). Quarterly excess returns, CAPM alphas, and Fama and French (2015) five-factor alphas are displayed in percentages. For the annual composite financial constraint index (FC index), we first build a firm-level FC index as the average z-score of cross-sectional ranks of the WW index (Whited and Wu, 2006), the HP index (Hadlock and Pierce, 2010), and the KZ index (Lamont et al., 2001) for the fiscal year ending in calendar year $t-1$ and then aggregate up to the portfolio level (which is formed at the beginning of each year t) by taking the median of long-leg firms minus the median of short-leg firms. *Average* is the portfolio that equally combines the anomalies in each panel. The sample period spans 1969Q1 to 2019Q4 for all but the failure probability anomaly (FProb), whose data begin in 1976Q1. Newey and West (1987) eight-lag adjusted t-statistics are in parentheses.

Anomaly	Excess return			CAPM alpha			FF5 alpha			FC index		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
					Panel A: Short leg more financially constrained							
ROA	1.92	1.15	0.77	0.26	−1.30	1.56	0.68	0.22	0.46	−0.31	0.56	−0.87
	(2.99)	(1.22)	(1.26)	(0.86)	(−2.25)	(2.51)	(2.45)	(0.53)	(0.98)	(−13.50)	(16.04)	(−17.40)
ROE	1.89	1.60	0.29	0.20	−0.84	1.04	0.07	0.51	−0.45	−0.25	0.58	−0.83
	(3.00)	(1.75)	(0.42)	(0.72)	(−1.41)	(1.43)	(0.34)	(1.17)	(−1.02)	(−5.78)	(14.84)	(−33.48)
OP	1.93	0.32	1.62	0.27	−2.00	2.27	0.76	−0.80	1.55	−0.26	0.51	−0.77
	(2.95)	(0.35)	(2.47)	(0.86)	(−3.53)	(3.45)	(2.93)	(−1.85)	(3.12)	(−13.97)	(23.93)	(−23.86)
Quality	2.34	0.35	1.99	0.72	−2.16	2.88	1.23	−1.48	2.71	−0.34	0.49	−0.83
	(3.60)	(0.36)	(2.76)	(2.49)	(−3.96)	(4.37)	(4.80)	(−3.54)	(5.21)	(−13.17)	(15.14)	(−15.04)
FProb	2.51	0.42	2.09	0.59	−3.36	3.95	0.74	−2.15	2.89	−0.62	0.51	−1.13
	(4.17)	(0.32)	(1.91)	(2.53)	(−3.71)	(4.12)	(1.97)	(−3.00)	(3.12)	(−8.89)	(18.82)	(−23.12)
O-Score	1.71	1.30	0.41	0.02	−1.17	1.19	0.79	−0.38	1.17	−0.42	0.59	−1.01
	(2.56)	(1.42)	(0.65)	(0.06)	(−2.34)	(1.94)	(2.56)	(−0.93)	(2.25)	(−7.44)	(32.08)	(−13.89)
TV	1.55	−0.09	1.64	0.38	−3.00	3.39	−0.35	−1.37	1.02	−0.55	0.59	−1.14
	(2.95)	(−0.08)	(1.74)	(1.44)	(−4.43)	(3.91)	(−1.31)	(−2.95)	(1.82)	(−5.09)	(18.81)	(−11.09)
IVOL	1.76	−0.26	2.01	0.48	−3.06	3.54	−0.28	−1.50	1.21	−0.62	0.60	−1.22
	(3.39)	(−0.25)	(2.17)	(1.93)	(−4.66)	(4.18)	(−1.40)	(−3.13)	(2.20)	(−5.24)	(18.68)	(−10.53)
Average	1.90	0.54	1.36	0.36	−2.06	2.42	0.45	−0.82	1.27	−0.42	0.55	−0.97
	(3.22)	(0.56)	(1.96)	(1.60)	(−3.76)	(3.68)	(2.37)	(−2.30)	(3.12)	(−22.82)	(27.22)	(−60.60)
					Panel B: Long leg more financially constrained							
BM	2.72	1.53	1.19	0.90	−0.29	1.18	0.25	0.27	−0.02	0.24	0.04	0.20
	(3.87)	(2.15)	(1.44)	(1.56)	(−0.81)	(1.40)	(0.57)	(1.13)	(−0.03)	(8.00)	(0.69)	(2.76)
LTR	2.43	1.82	0.62	0.22	−0.27	0.49	−0.08	0.49	−0.57	0.40	−0.33	0.73
	(2.94)	(2.34)	(0.69)	(0.30)	(−0.79)	(0.55)	(−0.14)	(1.47)	(−0.90)	(7.02)	(−6.10)	(8.38)
IA	2.29	1.14	1.15	0.38	−1.04	1.42	−0.21	0.01	−0.22	0.42	0.09	0.33
	(3.49)	(1.56)	(2.09)	(0.89)	(−2.76)	(2.46)	(−0.66)	(0.05)	(−0.57)	(31.21)	(2.44)	(8.85)
SIZE	1.99	1.61	0.38	−0.29	0.11	−0.41	0.09	0.22	−0.12	0.51	−1.17	1.69
	(2.35)	(2.70)	(0.45)	(−0.39)	(0.54)	(−0.43)	(0.34)	(2.30)	(−0.47)	(34.54)	(−37.69)	(61.31)
Average	2.36	1.52	0.84	0.30	−0.37	0.67	0.01	0.25	−0.23	0.39	−0.34	0.74
	(3.39)	(2.25)	(1.25)	(0.55)	(−1.50)	(0.97)	(0.05)	(1.56)	(−0.85)	(19.98)	(−15.98)	(23.09)

literature. For instance, the investment anomaly (IA) goes long decile with low asset growth firms and short decile with high asset growth firms. Table 2 reports the quarterly excess returns, CAPM alphas, and Fama–French five-factor alphas for these anomalies. As shown, the anomalies deliver positive return spreads and CAPM alphas except for the size anomaly, but not all Fama–French five-factor alphas are positive, as expected.

2.3. Evidence of differential financial constraints

To statistically verify that the long and short legs of these anomalies exhibit different degrees of financial constraints, we construct a composite financial constraint score based on three financial constraint indices extensively studied in the literature. First, the WW index (Whited and Wu, 2006) for firm i in year t is defined as

$$WW_{it} = -0.091CF_{it} - 0.062DIVPOS_{it} + 0.021TLTD_{it} - 0.044LNTA_{it} + 0.102ISG_{it} - 0.035SG_{it}, \quad (1)$$

where CF is cash flow scaled by total assets, $DIVPOS$ is an indicator that takes the value of one if the firm pays a dividend, $TLTD$ is long-term debt to total assets, $LNTA$ is the logarithm of total assets (in 1997

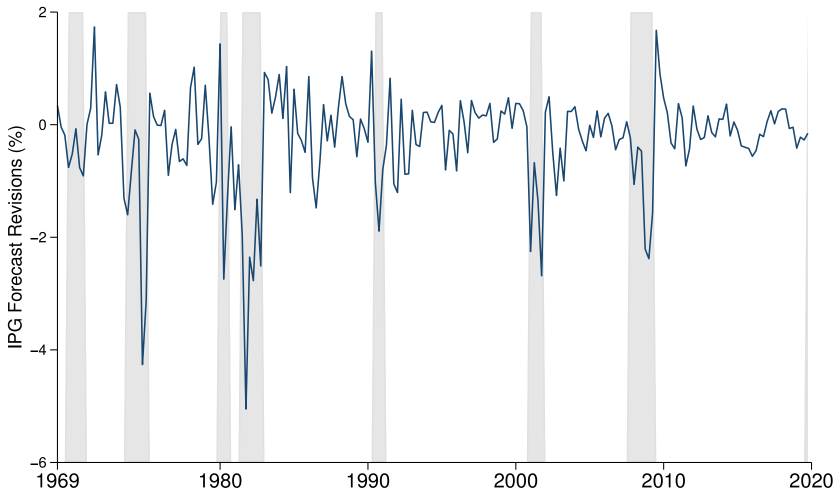

Fig. 1. IPG forecast revisions. This figure plots the revisions in expectations of one-quarter-ahead industrial production growth (IPG) from 1969Q1 to 2019Q4. IPG forecast revisions are computed from the Survey of Professional Forecasters (SPF) following Bordalo et al. (2020). Shaded bars indicate NBER recessions.

dollars), ISG is three-digit SIC industry sales growth, and SG is firm sales growth.

Second, we compute the HP index (Hadlock and Pierce, 2010) based on firm size and age:

$$HP_{it} = -0.737 LNTA_{it} + 0.043 LNTA_{it}^2 - 0.040 AGE_{it}, \tag{2}$$

where $LNTA$ is the logarithm of total assets (measured in 2004 dollars and capped at the log of \$4.5 billion), and AGE is the number of years that a firm appears in Compustat and is capped at 37 years.

Third, we follow the literature (Lamont et al., 2001; Farre-Mensa and Ljungqvist, 2016) and calculate the KZ index based on the regression coefficient estimates in Kaplan and Zingales (1997):

$$\begin{aligned} KZ_{it} = &-1.001909 CF_{it} + 0.2826389 Q_{it} + 3.139193 LEV_{it} \\ &- 39.3678 DIV_{it} - 1.314759 CASH_{it}, \end{aligned} \tag{3}$$

where CF is cash flow scaled by lagged property, plant, and equipment; Q is total assets plus the market value of equity minus the book value of common equity minus balance sheet deferred taxes divided by total assets; LEV is total debt scaled by total assets; DIV is dividend scaled by lagged property, plant, and equipment; and $CASH$ is cash and short-term investments scaled by lagged property, plant, and equipment.

Our annual firm-level composite financial constraint index is calculated as the average z-score of cross-sectional ranks of the three individual indices. Then the portfolio-level financial constraint is obtained as the median of the firms in each decile portfolio. The last three columns of Table 2 confirm that indeed the long legs of the profitability, quality, distress, and low-risk anomalies are on average less financially constrained than their corresponding short legs, whereas the long legs of the value, investment, and size anomalies are on average more financially constrained than their corresponding short legs.

2.4. Revisions in expectations of aggregate productivity

Our measures of revisions in expectations of aggregate productivity are constructed from the SPF database, which contains forecasts for a few important macroeconomic variables. Each quarter, the SPF polls professional economists on their forecasts about macroeconomic outcomes in the current and next four quarters, and the results are published around the end of the second month of the quarter (Bordalo et al., 2020; Han, 2021). For instance, the Federal Reserve Bank of Philadelphia published the results of the 2014Q4 SPF on November 17, 2014, which is in the middle of 2014Q4.

Standard macroeconomic models show that total factor productivity (TFP) shocks are important drivers of long-run economic growth and asset prices. However, the SPF does not provide forecasts for TFP, so we focus on the IPG forecast revisions to quantify changes in perceptions of macroeconomic productivity.[7] We use one-quarter-ahead forecast revisions to corroborate the horizons of anomaly returns. We follow Bordalo et al. (2020) and define the one-quarter-ahead forecast revision at quarter t as

$$Frev\_IPG_t = \mathbb{E}_t[IPG_{t+1}] - \mathbb{E}_{t-1}[IPG_{t+1}], \tag{4}$$

where IPG_{t+1} is the growth rate of the average industrial production index for quarter $t+1$. Accordingly, we designate a forecast revision as an upward (a downward) revision if it is positive (negative). Please refer to Bordalo et al. (2020) for an in-depth description. In particular, the forecast revision for quarter t is available in real-time as the SPF is typically published during quarter t (Bordalo et al., 2020; Han, 2021). We also note that the main results are robust to using alternative measures of macro productivity forecast revisions.[8]

Forecast revisions are crucial to equity valuations. Using different survey forecasts, De la and Myers (2021) and Bordalo et al. (2022) both conclude that (revisions in) subjective cash flow growth expectations explain most movements in the unexpected returns. Motivated by their findings, we hypothesize that forecast revisions of aggregate productivity can lead to forecast revisions of firms' earnings growth and thus induce potential mispricing at both the firm level and the portfolio level.

To understand how investors update beliefs about aggregate productivity, Fig. 1 plots the revisions in IPG expectations over time, with the shaded bars representing NBER recessions. Expectations are constantly revised over time. In addition, it appears that investors revise IPG

[7] We use forecast revisions for IPG rather than for real GDP growth because (i) IPG is less affected by developments in the financial industry that we exclude from anomaly construction, (ii) IPG is heavily studied in asset pricing literature (e.g., Chen et al., 1986 and Shen et al., 2017), and (iii) real GDP forecasts before 1992 are actually for real GNP and contain statistical noise. In addition, we do not use forecast revisions for CPI because its implications for productivity and asset prices are mixed: CPI could rise because of either stronger consumer demand or lower production. Consistently, we show in Table A6 in the Appendix that the predictive power remains when using revisions in real GDP growth forecasts but vanishes when using revisions in CPI forecasts.

[8] In addition to IPG forecast revisions, we verify that our main results are valid when using proxies for TFP forecast revisions in Table A1, unemployment rate forecast revisions in Table A2, the principal component of different forecast revisions in Table A3, and longer horizon macroeconomic forecasts in Table A4.

Table 3
Summary statistics for key variables.
The table displays the summary statistics. Panel A reports summary information of the key variables. Frev_IPG is the revision in consensus forecast of one-quarter-ahead industrial production growth from the Survey of Professional Forecasters, computed following Bordalo et al. (2020). Up_IPG is the indicator of an upward revision in expectations of one-quarter-ahead industrial production growth. Mktrf is the value-weighted return on the CRSP portfolio of US stocks in excess of the risk-free rate. SMB, HML, RMW, and CMA are the Fama and French (2015) size, value, profitability, and investment factors, respectively. Mktrf, SMB, HML, RMW, and CMA are from Kenneth French's website and compounded to quarterly percentages using monthly data. Sentiment is the quarterly average Baker and Wurgler (2006) investor sentiment index, taken from Jeffrey Wurgler's website. ρ is the first-order autocorrelation coefficient. Panel B reports the pairwise correlations between the time series, with p-values displayed in brackets. The sample is quarterly and spans from 1969Q1 to 2019Q4.

Panel A: Summary information

	Obs	Mean	Std. Dev.	Median	Min	Max	ρ
Frev_IPG	204	−0.28	0.90	−0.12	−5.05	1.74	0.35
Up_IPG	204	0.41	0.49	0.00	0.00	1.00	0.28
Mktrf	204	1.65	8.60	2.69	−26.46	23.17	0.05
SMB	204	0.38	5.38	−0.12	−12.38	16.52	−0.06
HML	204	0.96	5.99	0.57	−16.83	27.96	0.13
RMW	204	0.89	4.29	0.62	−14.60	27.00	0.12
CMA	204	0.93	4.07	0.24	−7.95	20.03	0.08
Sentiment	204	0.02	0.97	−0.01	−2.38	3.03	0.95

Panel B: Pairwise correlations

	Frev_IPG	Mktrf	SMB	HML	RMW	CMA	Sentiment
Frev_IPG	1.00						
Mktrf	0.03	1.00					
	[0.69]						
SMB	−0.07	0.41	1.00				
	[0.30]	[0.00]					
HML	0.06	−0.32	0.01	1.00			
	[0.38]	[0.00]	[0.91]				
RMW	0.01	−0.28	−0.19	0.10	1.00		
	[0.87]	[0.00]	[0.01]	[0.16]			
CMA	0.03	−0.42	−0.09	0.75	0.08	1.00	
	[0.72]	[0.00]	[0.22]	[0.00]	[0.27]		
Sentiment	−0.02	−0.10	−0.15	0.11	0.26	0.09	1.00
	[0.73]	[0.15]	[0.04]	[0.13]	[0.00]	[0.18]	

expectations downward at the onset of economic recessions. However, some periods (e.g., 1984Q4) are not identified as recessions but still experienced large downward revisions in productivity expectations.

2.5. Summary statistics

Summary statistics for the key variables are presented in Table 3 Panel A. In addition to forecast revisions, we report the summary statistics for the SMB, HML, RMW, and CMA factors taken from Kenneth French's website as the corresponding underlying anomalies are the focus of our study.

The mean IPG forecast revisions is –0.28%, which is statistically indistinguishable from zero. Moreover, IPG forecast revisions are not very persistent. Panel A shows that the first-order autocorrelation of IPG forecast revisions is 0.35, much smaller than the persistence of the Baker and Wurgler (2006) investor sentiment index (0.95), another leading anomaly predictor. The indicator of an upward IPG forecast revision is even less persistent (autocorrelation = 0.28). This low persistence implies that predictive regressions with forecast revisions are less prone to small sample bias for persistent predictors (Stambaugh, 1999).

Table 3 Panel B reports the pairwise correlations. IPG forecast revisions are materially uncorrelated with the Baker and Wurgler (2006) investor sentiment index, suggesting that investors' perceptions of aggregate productivity are not mere manifestations of stock market sentiment. We further compare the predictive ability of forecast revisions and investor sentiment in the next section and document their differences.

3. Main empirical findings

In this section, we perform a two-regime portfolio analysis and present the main empirical findings. Then we use predictive regressions to rule out compounding economic factors.

3.1. Average returns following upward and downward forecast revisions

We begin the empirical analysis by investigating the average returns following upward and downward forecast revisions. This classification method follows Baker and Wurgler (2006), who use a sentiment index to classify high- and low-sentiment periods.[9] The upward and downward forecast revisions offer a natural two-regime experiment that avoids the potential forward-looking bias incurred by the common practice that splits the sample based on unconditional percentiles. Specifically, we estimate the average returns following upward and downward revisions as estimates of a_U and a_D in the following regression:

$$R_{t+1} = a_U \cdot \mathbf{1}_{U,t} + a_D \cdot \mathbf{1}_{D,t} + \epsilon_{t+1}, \tag{5}$$

where $\mathbf{1}_{U,t}$ and $\mathbf{1}_{D,t}$ are, respectively, indicators for quarters with upward and downward revisions in expectations of industrial production growth, and R_{t+1} is the excess return on the long leg, the short leg, or the difference.

Table 4 reports the average portfolio returns for various anomalies across upward and downward forecast revision regimes. Panel A reports results for anomalies with more financially constrained short legs (i.e., profitability, quality, distress, and low-risk anomalies), and Panel B reports results for anomalies with more financially constrained long legs (i.e., value, investment, and size anomalies). Since size, value, profitability, and investment anomalies are the underlying basis for the prominent Fama and French (2015) five-factor model, we discuss the effect of IPG forecast revisions on these anomalies in more detail below. In Panel A, for example, the ROA anomaly spread is 2.84% per quarter following upward IPG forecast revisions, with a t-statistic of 3.74. Conversely, the ROA anomaly spread is –0.72% per quarter following downward IPG forecast revisions. Thus, the ROA anomaly is much

[9] See also Stambaugh et al. (2012), Birru (2018), and Chen et al. (2023) for two-regime analyses in anomaly prediction.

Table 4
Anomaly returns and productivity forecast revisions.
The table reports the average quarterly excess returns for anomalies following upward and downward revisions in expectations of industrial production growth (IPG). The average returns following upward and downward forecast revisions are estimates of a_U and a_D in the regression

$$R_{t+1} = a_U \cdot \mathbf{1}_{U,t} + a_D \cdot \mathbf{1}_{D,t} + \epsilon_{t+1},$$

where $\mathbf{1}_{U,t}$ and $\mathbf{1}_{D,t}$ are, respectively, indicators for quarters with upward and downward revisions in IPG expectations from the SPF survey, and R_{t+1} is the excess return on the long leg, the short leg, or the difference. Panel A reports results for anomalies with more financially constrained short legs, and Panel B reports results for anomalies with more financially constrained long legs. *Average* is the return to the portfolio that equally combines the anomalies in each panel. The sample period spans from 1969Q1 to 2019Q4 for all but the failure probability anomaly (FProb), whose data begin in 1976Q1. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

Anomaly	Long leg			Short leg			Long-Short		
	Up	Down	Up–Down	Up	Down	Up–Down	Up	Down	Up–Down
				Panel A: Short leg more financially constrained					
ROA	1.11	2.53	−1.42	−1.73	3.25	−4.97	2.84	−0.72	3.55
	(1.14)	(2.95)	(−1.13)	(−1.23)	(2.53)	(−2.70)	(3.74)	(−0.89)	(3.61)
ROE	0.99	2.59	−1.61	−1.49	3.85	−5.34	2.48	−1.26	3.74
	(1.09)	(2.95)	(−1.30)	(−1.06)	(3.00)	(−2.89)	(2.86)	(−1.40)	(3.50)
OP	1.27	2.45	−1.18	−2.71	2.53	−5.24	3.97	−0.08	4.06
	(1.25)	(2.78)	(−0.90)	(−2.11)	(1.97)	(−2.98)	(5.47)	(−0.10)	(4.49)
Quality	1.71	2.82	−1.11	−2.47	2.43	−4.90	4.18	0.39	3.79
	(1.74)	(3.37)	(−0.90)	(−1.78)	(1.79)	(−2.64)	(4.99)	(0.40)	(3.27)
FProb	1.82	3.00	−1.18	−3.65	3.30	−6.96	5.48	−0.30	5.78
	(1.90)	(3.49)	(−0.89)	(−1.97)	(1.92)	(−2.98)	(4.08)	(−0.21)	(3.37)
O-Score	0.86	2.34	−1.49	−1.88	3.65	−5.53	2.73	−1.31	4.04
	(0.81)	(2.68)	(−1.10)	(−1.49)	(2.75)	(−3.04)	(3.36)	(−1.64)	(3.78)
TV	1.29	1.78	−0.49	−2.71	1.87	−4.58	4.00	−0.09	4.09
	(1.94)	(2.45)	(−0.53)	(−1.84)	(1.23)	(−2.18)	(3.49)	(−0.07)	(2.53)
IVOL	1.43	2.02	−0.59	−2.65	1.52	−4.18	4.08	0.50	3.58
	(2.21)	(2.63)	(−0.59)	(−1.87)	(1.03)	(−2.09)	(3.50)	(0.41)	(2.34)
Average	1.26	2.39	−1.13	−2.46	2.74	−5.20	3.73	−0.35	4.07
	(1.48)	(2.94)	(−0.98)	(−1.84)	(2.05)	(−2.84)	(4.90)	(−0.38)	(3.97)
				Panel B: Long leg more financially constrained					
BM	0.51	4.34	−3.83	0.79	2.10	−1.31	−0.28	2.24	−2.52
	(0.58)	(3.60)	(−2.37)	(0.75)	(2.14)	(−0.92)	(−0.28)	(2.11)	(−2.02)
LTR	−0.58	4.61	−5.19	1.06	2.46	−1.41	−1.63	2.15	−3.78
	(−0.54)	(3.41)	(−2.82)	(0.87)	(2.31)	(−0.86)	(−2.01)	(1.85)	(−3.31)
IA	−0.34	4.20	−4.54	0.20	1.91	−1.72	−0.53	2.29	−2.82
	(−0.38)	(3.96)	(−3.16)	(0.17)	(1.94)	(−1.12)	(−0.76)	(3.25)	(−3.19)
SIZE	−1.70	4.70	−6.40	1.05	2.03	−0.97	−2.75	2.67	−5.43
	(−1.51)	(3.74)	(−3.72)	(1.27)	(2.49)	(−0.88)	(−3.32)	(2.54)	(−5.11)
Average	−0.53	4.46	−4.99	0.77	2.13	−1.35	−1.30	2.34	−3.64
	(−0.58)	(3.89)	(−3.19)	(0.75)	(2.28)	(−0.97)	(−2.13)	(2.78)	(−4.73)

stronger following upward revisions in IPG expectations than following downward revisions. Interestingly, most of the predictive power for profitability, quality, distress, and low-risk anomalies is derived from the short leg, suggesting that low-profitability firms, low-quality firms, financially distressed firms, and risky firms face more financial frictions and are more sensitive to changes in investors' perceptions. The last column reports the difference in the ROA anomaly spread between upward and downward IPG forecast revisions, which is 3.55% per quarter (t-statistic = 3.61). Considering that the average ROA anomaly spread is only 0.77% per quarter, the 3.55% difference is also of economic significance.

For the remaining profitability, quality, distress, and low-risk anomalies, we also observe that the short legs earn significantly lower returns following upward IPG forecast revisions than following downward revisions. As indicated at the bottom of Panel A, the average return spread of profitability, quality, distress, and low-risk anomalies is 3.73% per quarter following upward IPG forecast revisions and –0.35% per quarter following downward revisions.

The results for value, investment, and size anomalies reveal the opposite predictive power of IPG forecast revisions. Table 4 Panel B shows that the BM anomaly spread is –0.28% per quarter following upward IPG forecast revisions; conversely, it is 2.24% per quarter following downward revisions, implying a difference of –2.52% (t-statistic = –2.02). This variation in the BM premium is mainly derived from the more financially constrained long leg, which earns 0.51% per quarter following upward IPG forecast revisions and 4.34% per quarter following downward revisions. We observe a similar pattern among the LTR, IA, and SIZE anomalies. For example, the size anomaly spread is –2.75% per quarter following upward IPG forecast revisions and 2.67% per quarter following downward revisions. This evidence is consistent with the conjecture that value, low-investment, and small firms that face more financial frictions tend to experience more severe financial constraints and undervaluation when investors turn pessimistic about future productivity.

Since data on TFP growth forecasts are not available, we use IPG forecasts as substitutes. Relevant theoretical models, such as Bordalo et al. (2021), Gulen et al. (2023), and Deng (2023), assume that investors extrapolate TFP growth and verify their assumptions using data on earnings growth forecasts due to the lack of TFP forecasts. In addition, other earlier studies such as Gourio (2006), Imrohoroglu and Tuzel (2014), and Novy-Marx (2013) proxy for the unobserved productivity with measures related to earnings or cash flow. Therefore, constrained by the availability of a long time series of TFP growth forecasts, we also adopt IPG forecasts as our imperfect proxy.[10] In addition to using IPG expectations to proxy for aggregate productivity, we use expectations of the unemployment rate (UR) as a robustness check in Table A2. The profitability, quality, distress, and low-risk anomalies are more pronounced following downward UR forecast revisions; conversely, value, investment, and size anomalies are more pronounced following

[10] In Table A1, we construct an alternative proxy for TFP forecast revisions, $Frev\_TFP_{2,t}$. As investors make forecast revisions in response to shocks in expectations, we project the IPG forecast revisions on the TFP shock and its lag to filter out TFP forecast revisions. We then calculate $Frev\_TFP_{2,t}$ as the fitted values of projecting IPG forecast revisions onto the realized TFP shock and its lag. The TFP shock is determined by modeling TFP growth as an AR(1) process and taking the residual. The fitted value may be less susceptible to shocks that are not related to aggregate productivity and can thus serve as a proxy for investors' TFP forecast revisions. The results of this approach are reported in columns (4) to (6) of Table A1 and are qualitatively similar.

Table 5
CAPM-adjusted anomaly returns and productivity forecast revisions.
The table reports the average quarterly CAPM-adjusted returns for anomalies following upward and downward revisions in expectations of industrial production growth (IPG). The average returns following upward and downward forecast revisions are estimates of a_U and a_D in the regression

$$R_{t+1} = a_U \cdot \mathbf{1}_{U,t} + a_D \cdot \mathbf{1}_{D,t} + b \cdot Mktrf_{t+1} + \epsilon_{t+1},$$

where $\mathbf{1}_{U,t}$ and $\mathbf{1}_{D,t}$ are, respectively, indicators for quarters with upward and downward revisions in IPG expectations from the SPF survey, $Mktrf_{t+1}$ is the market factor, and R_{t+1} is the excess return on the long leg, the short leg, or the difference. Panel A reports results for anomalies with more financially constrained short legs, and Panel B reports results for anomalies with more financially constrained long legs. *Average* is the return to the portfolio that equally combines the anomalies in each panel. The sample period spans from 1969Q1 to 2019Q4 for all but the failure probability anomaly (FProb), whose data begin in 1976Q1. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

Anomaly	Long leg			Short leg			Long-Short		
	Up	Down	Up–Down	Up	Down	Up–Down	Up	Down	Up–Down
Panel A: Short leg more financially constrained									
ROA	0.44	0.11	0.33	−2.70	−0.27	−2.43	3.14	0.38	2.75
	(1.10)	(0.31)	(0.72)	(−4.05)	(−0.37)	(−2.87)	(4.62)	(0.48)	(3.10)
ROE	0.31	0.14	0.17	−2.46	0.33	−2.80	2.77	−0.19	2.97
	(0.94)	(0.39)	(0.42)	(−3.41)	(0.44)	(−3.08)	(3.47)	(−0.21)	(3.00)
OP	0.60	0.02	0.57	−3.63	−0.79	−2.83	4.22	0.82	3.41
	(1.37)	(0.06)	(1.20)	(−5.91)	(−1.16)	(−4.06)	(6.03)	(1.01)	(4.05)
Quality	1.06	0.46	0.59	−3.47	−1.19	−2.28	4.53	1.65	2.88
	(2.56)	(1.34)	(1.23)	(−5.40)	(−1.63)	(−2.64)	(5.91)	(1.88)	(2.76)
FProb	0.87	0.37	0.50	−5.49	−1.77	−3.72	6.36	2.15	4.21
	(1.95)	(1.42)	(0.93)	(−5.79)	(−1.52)	(−2.91)	(5.68)	(1.73)	(2.77)
O-Score	0.18	−0.13	0.30	−2.86	0.09	−2.95	3.03	−0.22	3.25
	(0.36)	(−0.37)	(0.59)	(−4.75)	(0.14)	(−3.47)	(3.67)	(−0.30)	(3.16)
TV	0.82	0.07	0.74	−3.88	−2.35	−1.53	4.70	2.42	2.28
	(2.44)	(0.23)	(2.03)	(−4.89)	(−2.38)	(−1.23)	(5.00)	(2.01)	(1.63)
IVOL	0.92	0.16	0.75	−3.77	−2.53	−1.24	4.69	2.69	2.00
	(2.58)	(0.57)	(1.89)	(−4.57)	(−2.69)	(−1.00)	(4.74)	(2.32)	(1.40)
Average	0.64	0.15	0.49	−3.50	−1.00	−2.49	4.14	1.15	2.99
	(2.20)	(0.56)	(1.49)	(−6.20)	(−1.40)	(−3.20)	(6.43)	(1.36)	(3.44)
Panel B: Long leg more financially constrained									
BM	−0.21	1.71	−1.92	0.06	−0.55	0.61	−0.28	2.26	−2.53
	(−0.35)	(2.08)	(−2.07)	(0.13)	(−1.37)	(1.17)	(−0.28)	(2.08)	(−2.02)
LTR	−1.46	1.43	−2.89	0.22	−0.57	0.79	−1.68	2.00	−3.68
	(−2.34)	(1.43)	(−3.01)	(0.46)	(−1.29)	(1.21)	(−2.04)	(1.76)	(−3.25)
IA	−1.09	1.47	−2.56	−0.68	−1.27	0.59	−0.41	2.73	−3.14
	(−2.44)	(2.72)	(−4.50)	(−1.39)	(−2.47)	(0.89)	(−0.60)	(3.51)	(−3.54)
SIZE	−2.60	1.44	−4.04	0.45	−0.16	0.61	−3.05	1.60	−4.65
	(−3.80)	(1.49)	(−4.21)	(1.71)	(−0.79)	(2.76)	(−3.55)	(1.42)	(−4.56)
Average	−1.34	1.51	−2.85	0.01	−0.64	0.65	−1.35	2.15	−3.50
	(−2.98)	(2.08)	(−4.26)	(0.03)	(−2.15)	(1.60)	(−2.12)	(2.50)	(−4.59)

upward UR forecast revisions. We provide further robustness checks using a composite measure of perceived macroeconomic conditions. Specifically, we form a composite index for perceived macroeconomic conditions based on the first principal component of IPG forecast revisions, the negative of UR forecast revisions, and real GDP growth forecast revisions. We then split the sample into positive and negative subsamples based on this composite index and find similar results (Table A3).

We perform additional analysis in Table 5 by replacing excess returns with CAPM-adjusted returns in Eq. (5). The results in Table 5 indicate that the predictive ability of IPG forecast revisions remains robust when we perform the two-regime analysis based on CAPM-adjusted returns. The average CAPM alpha of profitability, quality, distress, and low-risk anomalies is 4.14% per quarter following upward IPG forecast revisions and 1.15% per quarter following downward revisions. On the other hand, the average CAPM alpha of value, investment, and size anomalies is –1.35% per quarter following upward IPG forecast revisions and 2.15% per quarter following downward revisions. As shown, this two-regime pattern remains robust when using CAPM alphas. Finally, note that we do not use Fama and French (2015) five-factor adjusted returns to perform the two-regime analysis. This is because the underlying factors, such as SMB, HML, RMW, and CMA, are themselves the object of this study and exhibit a strong two-regime pattern; thus, controlling for them would make the results uninterpretable. Earlier related studies also avoid adjusting for underlying factors. For example, Cassella et al. (2022) report CAPM alpha since they focus on the value premium. Similarly, Baker and Wurgler (2006) exclude SMB and HML from their factors when size and value are the portfolios being forecasted by sentiment.

In summary, the results of the two-regime analysis suggest that revisions in aggregate productivity forecasts positively predict profitability, quality, distress, and low-risk anomalies but negatively predict value, investment, and size anomalies. Similar to Stambaugh et al. (2012), we do not provide explanations for unconditional anomaly returns in the first place. Rather, we study how the conditional anomaly returns vary with revisions in expectations of macroeconomic conditions.

3.2. Predictive regressions

The two-regime analysis in the previous section provides intuitive and easy-to-interpret results. In this section, we proceed with predictive regressions, which help to not only strengthen the previous findings on anomaly predictability but also rule out compounding economic factors and alternative explanations at the same time.

We begin by considering the following standard predictive regression:

$$R_{t+1} = \alpha + \beta Frev\_IPG_t + \gamma Mktrf_{t+1} + \epsilon_{t+1}, \tag{6}$$

where $Frev\_IPG_t$ is the IPG forecast revisions, $Mktrf_{t+1}$ is the market factor, and R_{t+1} is the excess return on the long leg, the short leg, or the difference. The estimation results are presented in Table 6 and are in line with the two-regime analysis in Table 4. The bottom of Table 6 Panel A shows that a one-standard-deviation increase in IPG forecast revisions is associated with a 0.89% decrease in the long legs of the profitability, quality, distress, and low-risk anomalies. On the other hand, IPG forecast revisions have much stronger effect on the short legs of these anomalies. A one-standard-deviation increase in IPG forecast revisions is associated with a 2.93% decrease in the short leg of the equally combined portfolio (t-statistic = 1.98). Conversely,

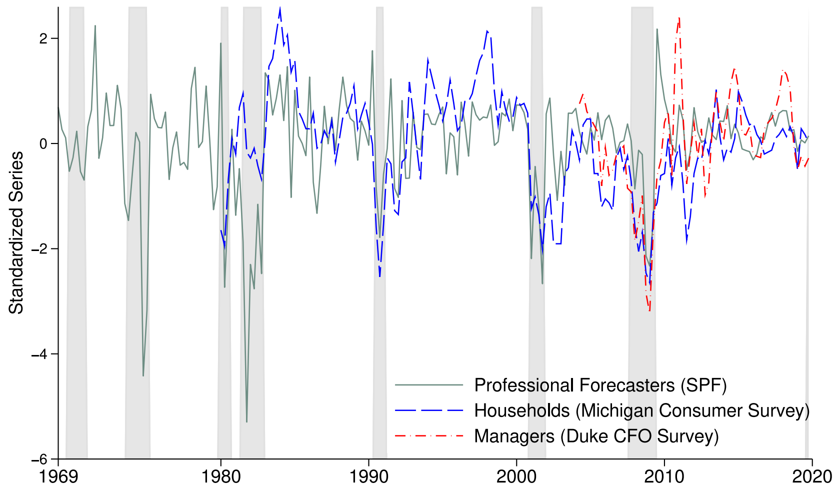

Fig. 2. Comparing the SPF with the Michigan Consumer Survey and Duke CFO Survey. This figure shows the revisions in expectations of macroeconomic conditions from different surveys, which are standardized to have zero mean and unit variance. The solid line plots the revisions in expectations of one-quarter-ahead industrial production growth from the SPF. The dashed line plots the relative score for business conditions expected during the next year minus the relative score for business conditions expected during the next five years, surveyed two years ago from the Michigan Consumer Survey. The dash-dotted line plots the average optimism level about the US economy minus that surveyed two years ago from the Duke CFO Survey. The sample size depends on availability. Shaded bars indicate NBER recessions.

Panel B shows that IPG forecast revisions have stronger effects on the long legs of value, investment, and size anomalies than their short legs. As shown in the bottom of Panel B, a one-standard-deviation increase in IPG forecast revisions leads to a 3.27% (0.99%) decrease in the long leg (short leg) of the equally combined portfolio of value, investment, and size anomalies. In addition, when the market factor is included in the regression, the coefficients on IPG forecast revisions are slightly lower but remain statistically significant. Overall, the results suggest that macroeconomic perceptions have stronger effects on the financially constrained (unprofitable, low-quality, distressed, risky, value, low-investment, and small) firms, consistent with our financial-constraint-based explanation.

In the Appendix, we further analyze the robustness of anomaly predictability by revisions in expectations of aggregate productivity. First, using revisions of longer horizon forecasts from the SPF reaches similar conclusion (Table A4), which is not surprising as productivity forecasts for different horizons are highly correlated. Second, we find that the predictive power is not limited to the SPF, which surveys professional macroeconomic forecasters. As shown in Fig. 2, professional forecasters, households, and corporate managers tend to revise their expectations of aggregate productivity in lockstep. Table A5 further shows that the revisions in expectations of future business conditions or the country's overall economy, as reported by the households in the Michigan Survey of Consumers and managers in the Duke CFO Survey, yield similar results in predicting anomalies. Third, we experiment with forecast revisions for alternative macro variables. Table A6 shows that the predictive power remains when using revisions in real GDP growth forecasts but vanishes when using revisions in CPI forecasts. This is as expected since increases in inflation could be either good or bad news of macroeconomic conditions. These tests provide further evidence that our baseline result is driven by perceptions of aggregate productivity rather than by perceptions of inflation.

We next consider the bivariate predictive regressions that control for other prominent anomaly predictors:

$$R_{t+1} = \alpha + \beta Frev\_IPG_t + \gamma z_t + \epsilon_{t+1}, \tag{7}$$

where $Frev\_IPG_t$ is the IPG forecast revisions, z_t is the control variable, and R_{t+1} is the excess return on the long leg, the short leg, or the difference. Table 7 presents the estimation results for the bivariate predictive regressions. We detail the selection of the control variables below.

Previous studies suggest that investor sentiment can predict many anomalies (Baker and Wurgler, 2006; Stambaugh et al., 2012). Following favorable macroeconomic shocks, investors may revise their productivity expectations upward and become too optimistic in the meantime (i.e., elevated investor sentiment). To account for this possibility, we control for the Baker and Wurgler (2006) investor sentiment index and report the results in columns (1) and (2) of Table 7. As shown, the coefficients on sentiment are insignificant when predicting value and investment anomalies. However, the coefficients on IPG forecast revisions remain similarly significant. One could view investor sentiment as a broad concept related to misperception (Baker and Wurgler, 2006), whereas the revisions in expectations of aggregate productivity have more concrete economic interpretations. As previously shown in Table 3 Panel B, IPG forecast revisions are statistically uncorrelated with investor sentiment, indicating that they are relatively orthogonal variables in predicting anomaly returns. Thus, the results above indicate that macroeconomic productivity expectations contain information beyond stock market sentiment. More important, Stambaugh et al. (2012) suggest that investor sentiment should positively predict all anomalies as mispricing tends to be more severe during high-sentiment periods than during low-sentiment periods because of short-sale impediments. However, IPG forecast revisions positively predict profitability, quality, distress, and low-risk anomalies and negatively predict value, investment, and size anomalies.

The inverse of the surplus consumption ratio has been used as a proxy for effective risk aversion (Campbell and Cochrane, 1999; Wachter, 2006). Following Wachter (2006), we compute the surplus consumption ratio as the history of the average past real consumption growth rate. Upward IPG forecast revisions may coincide with low effective risk aversion. Hence, if an anomaly is driven by risk, then the surplus consumption ratio should negatively predict its returns. To rule out the possibility that the predictive power of IPG forecast revisions derives from its correlation with the surplus consumption ratio, we include the surplus ratio in the bivariate regression of Eq. (7). Columns (3) and (4) of Table 7 show that the coefficient on the surplus consumption ratio is either insignificant or has the wrong sign. Moreover, after including the surplus consumption ratio, IPG forecast revisions remain significant. Under a fully rational framework, the potential positive correlation between IPG forecast revisions and the surplus consumption ratio would imply that IPG forecast revisions should predict all the anomaly returns with the same negative sign. However, we find that IPG forecast revisions positively predict profitability, quality, distress,

Table 6
Predictive regressions.
The table reports estimates of β in the following predictive regression:

$$R_{t+1} = \alpha + \beta Frev\_IPG_t + \gamma Mktrf_{t+1} + \epsilon_{t+1},$$

where $Frev\_IPG_t$ is the revision in expectations of industrial production growth from the SPF survey, $Mktrf_{t+1}$ is the market factor, and R_{t+1} is the quarterly excess return on the long leg, the short leg, or the difference. Panel A reports results for anomalies with more financially constrained short legs, and Panel B reports results for anomalies with more financially constrained long legs. *Average* is the return to the portfolio that equally combines the anomalies in each panel. Columns (1) to (3) report results for excess returns, and columns (4) to (6) report results for CAPM-adjusted returns. All regressions include standardized independent variables with zero mean and unit variance. The sample period spans from 1969Q1 to 2019Q4 for all but the failure probability anomaly (FProb), whose data begin in 1976Q1. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

Anomaly	Excess return			CAPM alpha		
	Long leg (1)	Short leg (2)	Long-Short (3)	Long leg (4)	Short leg (5)	Long-Short (6)
Panel A: Short leg more financially constrained						
ROA	−1.07	−2.71	1.64	0.02	−1.12	1.14
	(−1.44)	(−2.53)	(3.06)	(0.09)	(−2.41)	(2.44)
ROE	−1.11	−3.09	1.98	−0.00	−1.51	1.50
	(−1.25)	(−2.53)	(3.27)	(−0.01)	(−3.16)	(2.77)
OP	−1.02	−2.63	1.60	0.07	−1.12	1.19
	(−1.33)	(−2.37)	(3.00)	(0.33)	(−3.31)	(2.76)
Quality	−1.03	−2.87	1.83	0.03	−1.24	1.27
	(−1.52)	(−1.95)	(1.88)	(0.10)	(−2.29)	(1.75)
FProb	−0.34	−2.67	2.32	0.14	−1.73	1.86
	(−0.60)	(−1.27)	(1.24)	(0.39)	(−1.39)	(1.24)
O-Score	−1.07	−2.90	1.82	0.04	−1.29	1.33
	(−1.45)	(−1.95)	(2.07)	(0.18)	(−2.66)	(2.12)
TV	−0.48	−2.97	2.49	0.29	−1.07	1.37
	(−0.88)	(−1.49)	(1.46)	(1.22)	(−1.08)	(1.13)
IVOL	−0.50	−2.83	2.33	0.34	−1.01	1.35
	(−0.92)	(−1.49)	(1.48)	(1.49)	(−1.08)	(1.19)
Average	−0.89	−2.93	2.04	0.13	−1.24	1.37
	(−1.31)	(−1.98)	(2.11)	(0.65)	(−2.19)	(1.99)
Panel B: Long leg more financially constrained						
BM	−2.33	−0.88	−1.45	−1.15	0.32	−1.47
	(−1.96)	(−0.90)	(−2.42)	(−2.26)	(0.99)	(−2.30)
LTR	−4.24	−0.85	−3.39	−2.83	0.53	−3.35
	(−2.39)	(−0.82)	(−3.20)	(−3.37)	(1.37)	(−3.34)
IA	−2.74	−1.51	−1.23	−1.51	−0.08	−1.43
	(−2.42)	(−1.19)	(−3.13)	(−4.02)	(−0.19)	(−3.73)
SIZE	−3.77	−0.70	−3.06	−2.30	0.28	−2.59
	(−2.63)	(−0.98)	(−3.65)	(−4.08)	(2.85)	(−4.14)
Average	−3.27	−0.99	−2.28	−1.95	0.26	−2.21
	(−2.41)	(−1.00)	(−4.25)	(−3.87)	(1.04)	(−4.33)

and low-risk anomalies and negatively predict value, investment, and size anomalies.

In addition, previous literature documents that anomaly return volatility (Moreira and Muir, 2017), anomaly value spread (Cohen et al., 2003), degree of extrapolative weighting (He et al., 2023), and return dispersion (Stivers and Sun, 2010) can predict anomaly returns. We thus also control for these anomaly predictors in turn and reach similar conclusion, as evidenced in the remaining columns of Table 7.

IPG forecast revisions could closely track the realized productivity shocks. In Bayesian updating, investors revise their expectations toward the new signals based on the shocks that they receive, with the learning rate being the signal-to-noise ratio. However, survey evidence (e.g., Bordalo et al., 2019, 2021) shows that investors tend to exaggerate the learning rate relative to Bayesian updating, suggesting an overreaction. It is hence interesting to compare the predictive ability of forecast revisions and realized shocks. If anomaly returns are driven by realized macroeconomic shocks rather than by forward-looking macroeconomic beliefs, then realized shocks should subsume the predictive power of forecast revisions.[11]

We report the results in Table A7 by estimating equation (7) with realized productivity shocks as controls. We observe two main patterns. First, when using realized productivity shocks in univariate predictive regressions, their coefficients are insignificant, demonstrating little predictive power for the anomalies. Second, when used in bivariate regressions, the coefficients on realized productivity shocks even flip signs in several cases. In contrast, the coefficients on IPG forecast revisions remain statistically significant. Thus, the horse race regression results indicate that forward-looking investor perceptions, rather than realized outcomes, drive the time variation in anomaly returns.

To further test whether these anomalies are explained by macroeconomic risk, we control for a host of 16 macro predictors in Table A8. Specifically, we include the 15 equity premium predictors studied in Welch and Goyal (2008), along with the economic uncertainty index (UNC) of Jurado et al. (2015).[12] In line with Table 6, we still find that IPG forecast revisions predict stronger profitability, quality, distress, and low-risk anomalies but weaker value, investment, and size anomalies. However, the coefficients for the macro variables are generally insignificant at conventional significance levels, indicating a

[11] To provide a fair comparison, we collect initial releases from the Real-Time Data Set for Macroeconomists at the Federal Reserve Bank of Philadelphia to construct the realized industrial production growth rate. Following Lochstoer and Tetlock (2020), we then proxy for the realized productivity shocks as the residuals of modeling industrial production growth as an AR(1) process.

[12] Table A8 controls for the lagged 16 macro predictors in turn: log dividend price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend–payout ratio (DE), stock variance (SVAR), cross-sectional premium (CSP), book-to-market ratio (BM), net equity issuance (NTIS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), inflation (INFL), and economic uncertainty index (UNC).

Table 7
Predictive regressions: Controlling for confounding variables.
The table reports estimates of β and γ in the following bivariate predictive regression:

$$R_{t+1} = \alpha + \beta Frev\_IPG_t + \gamma z_t + \epsilon_{t+1},$$

where $Frev\_IPG_t$ is the revision in expectations of industrial production growth, z_t is the control variable, and R_{t+1} is the quarterly excess return on the long-short anomalies. The control variable z_t is the average Baker and Wurgler (2006) investor sentiment index in columns (1) and (2), the surplus consumption ratio calculated following Wachter (2006) in columns (3) and (4), the Cassella and Gulen (2018) degree of extrapolative weighting (DOX) in columns (5) and (6), the Stivers and Sun (2010) return dispersion in columns (7) and (8), the anomaly's value spread $[\log(\mathrm{BM})_{\mathrm{long}} - \log(\mathrm{BM})_{\mathrm{short}}]$ in columns (9) and (10), and the realized volatility of daily anomaly returns in columns (11) and (12). All regressions include standardized independent variables with zero mean and unit variance. Panels A and C (Panels B and D) report results for anomalies with more financially constrained short legs (long legs). *Average* is the portfolio that equally combines the anomalies in each panel. The sample period spans from 1969Q1 to 2019Q4, and the DOX data, obtained from Cooper et al. (2024), ends in 2018Q4. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

z_t =	Sentiment		Surplus ratio		DOX	
	β (1)	γ (2)	β (3)	γ (4)	β (5)	γ (6)
Panel A: Short leg more financially constrained						
ROA	1.69	2.25	1.66	0.51	1.70	0.21
	(3.32)	(4.29)	(3.02)	(0.89)	(3.26)	(0.25)
ROE	2.03	2.27	1.99	0.36	2.06	0.30
	(3.49)	(3.86)	(3.22)	(0.65)	(3.38)	(0.31)
OP	1.65	1.98	1.60	0.04	1.57	−0.11
	(3.50)	(5.11)	(2.95)	(0.07)	(2.93)	(−0.17)
Quality	1.89	2.41	1.85	0.28	1.92	0.28
	(2.31)	(4.70)	(1.86)	(0.39)	(2.08)	(0.33)
FProb	2.92	5.52	2.35	0.55	2.72	1.13
	(1.68)	(4.48)	(1.23)	(0.41)	(1.48)	(0.84)
O-Score	1.87	2.01	1.85	0.71	1.79	−0.10
	(2.62)	(3.88)	(2.03)	(1.20)	(2.14)	(−0.16)
TV	2.58	3.40	2.54	0.96	2.77	0.98
	(1.71)	(4.17)	(1.45)	(1.24)	(1.75)	(0.82)
IVOL	2.41	3.17	2.38	1.02	2.52	0.67
	(1.75)	(3.93)	(1.47)	(1.38)	(1.69)	(0.56)
Average	2.11	2.65	2.07	0.56	2.16	0.40
	(2.56)	(4.86)	(2.07)	(0.90)	(2.38)	(0.45)
Panel B: Long leg more financially constrained						
BM	−1.46	−0.46	−1.41	0.97	−1.07	1.36
	(−2.46)	(−0.63)	(−2.42)	(1.30)	(−1.53)	(1.80)
LTR	−3.41	−0.68	−3.36	0.65	−3.04	1.27
	(−3.35)	(−0.78)	(−3.25)	(0.88)	(−2.50)	(1.67)
IA	−1.23	0.17	−1.22	0.36	−1.10	0.49
	(−3.14)	(0.29)	(−3.04)	(0.81)	(−2.35)	(0.72)
SIZE	−3.11	−1.80	−3.06	0.09	−2.81	0.90
	(−4.25)	(−2.29)	(−3.62)	(0.13)	(−3.28)	(1.20)
Average	−2.30	−0.69	−2.26	0.52	−2.00	1.00
	(−4.63)	(−1.13)	(−4.33)	(0.94)	(−3.17)	(1.58)

z_t =	Return dispersion		Value spread		Realized volatility	
	β (7)	γ (8)	β (9)	γ (10)	β (11)	γ (12)
Panel C: Short leg more financially constrained						
ROA	1.74	0.48	1.50	0.81	1.69	0.65
	(2.90)	(0.66)	(2.64)	(1.23)	(2.93)	(0.81)
ROE	2.02	0.19	1.73	1.16	2.02	0.49
	(3.06)	(0.21)	(2.77)	(1.70)	(3.16)	(0.47)
OP	1.64	0.16	1.57	0.33	1.61	0.06
	(2.84)	(0.25)	(2.90)	(0.61)	(2.90)	(0.09)
Quality	1.81	−0.14	1.63	0.93	1.75	−0.75
	(1.83)	(−0.14)	(1.64)	(1.38)	(1.90)	(−0.97)
FProb	2.25	−0.45	1.84	2.84	2.36	−0.20
	(1.23)	(−0.23)	(1.09)	(2.20)	(1.20)	(−0.09)
O-Score	1.77	−0.27	1.74	0.49	1.77	−0.85
	(1.97)	(−0.49)	(1.95)	(0.75)	(2.06)	(−1.51)
TV	2.39	−0.51	1.97	3.08	2.31	−0.96
	(1.40)	(−0.31)	(1.39)	(3.33)	(1.35)	(−0.50)
IVOL	2.29	−0.19	1.81	3.33	2.30	−0.17
	(1.43)	(−0.12)	(1.46)	(3.64)	(1.42)	(−0.09)
Average	2.02	−0.10	1.60	1.83	2.01	−0.19
	(2.03)	(−0.09)	(1.80)	(2.45)	(2.02)	(−0.16)
Panel D: Long leg more financially constrained						
BM	−1.19	1.24	−1.44	0.11	−1.39	0.39
	(−2.02)	(2.27)	(−2.36)	(0.10)	(−2.32)	(0.58)
LTR	−3.08	1.49	−3.34	0.70	−3.31	0.36
	(−2.97)	(2.84)	(−3.22)	(0.67)	(−3.00)	(0.49)
IA	−1.08	0.72	−1.19	0.31	−1.17	0.39
	(−2.45)	(1.57)	(−2.95)	(0.65)	(−2.66)	(0.63)
SIZE	−2.72	1.66	−2.92	2.03	−2.86	1.33
	(−3.74)	(2.75)	(−4.45)	(3.00)	(−3.57)	(2.11)
Average	−2.02	1.28	−2.18	0.91	−2.16	0.64
	(−4.03)	(3.05)	(−4.25)	(1.16)	(−3.91)	(1.08)

weak connection between expected anomaly returns and these realized economic indicators (Cochrane, 2017; Bender et al., 2018; Giglio et al., 2021).[13]

Thus far, the results from various predictive regressions deliver the same message as the comparisons between upward and downward forecast revisions in Table 4. More important, these results help exclude purely risk-based explanations since we show that our results remain largely unchanged after controlling for various proxies for time variation in risk aversion, time-varying amount of risk, and business cycle variables. These control variables have little power in predicting anomaly returns, or exhibit the opposite sign as implied by rational theory. In addition, we find little evidence that IPG forecast revisions predict the anomaly returns by predicting the time-varying betas of their constituents (Table A9). We also show in Section 4 that IPG forecast revisions can predict expectation errors in firms' long-term earnings growth, which is hard to reconcile under a rational framework. These findings, taken together, indicate that the predictive power of IPG forecast revisions is unlikely driven by effective risk aversion, market risk, macroeconomic risk, and macroeconomic uncertainty. It is still possible that there exist certain "omitted" risks that would explain our results. However, the risk-based model needs to explain why the unconstrained firms (which are on average less risky) become more risky and thus earn higher returns in good times (i.e., following upward IPG forecast revisions), which also appears to be hard to reconcile.

Recent studies (e.g., Welch and Goyal, 2008) suggest that in-sample analysis does not guarantee out-of-sample forecasting ability. We thus follow Chen et al. (2022) and assess the predictive performance of IPG forecast revisions with out-of-sample tests. Table A10 reports the out-of-sample predictability. We find that $Frev\_IPG$ performs significantly better than the historical average in forecasting the average anomaly returns. For anomalies with financially constrained short legs, the out-of-sample R^2 for $Frev\_IPG$ is 5.6% (p-value = 0.01) for the expanding-window approach and 7.5% (p-value = 0.02) for the rolling-window approach. Similarly, for anomalies with financially constrained long legs, the out-of-sample R^2 is 8.3% (p-value < 0.01) for the expanding-window approach and 6.8% (p-value < 0.01) for the rolling-window approach. However, the out-of-sample performance for other predictors is mixed. For example, the Baker and Wurgler (2006) investor sentiment index exhibits stronger (weaker) predictability than the historical average returns for anomalies with more financially constrained short (long) legs. Overall, the forecasting power of $Frev\_IPG$ compares favorably with the other predictors, judging by their out-of-sample R^2s, thereby validating the in-sample performance of $Frev\_IPG$.

3.3. Implications for factor investing

Having confirmed the predictive power of IPG forecast revisions, one might wonder whether we can use the predictive power of macro forecast revisions to enhance the performance of existing factors. In this subsection, we propose a factor rotation strategy based on the direction of the previous quarter's IPG forecast revisions. Specifically, the factor rotation strategy invests in an equal combination of profitability, quality, distress, and low-risk anomalies following upward IPG forecast revisions in the previous quarter, and an equal combination of value, investment, and size anomalies otherwise. If IPG forecast revisions can predict the anomalies, then this factor rotation strategy should outperform the original anomalies.

To provide a visual impression, Fig. 3 plots the cumulative excess portfolio returns to the factor rotation strategy against the cumulative average returns of profitability, quality, distress, and low-risk anomalies as well as the cumulative average returns of value, investment, and size anomalies. From this figure, we can see that the factor rotation strategy earns higher returns than both equal combination strategies. To further statistically assess the performance, we report the CAPM alpha, Fama and French (2015) five-factor alpha, and Sharpe ratio for this factor rotation strategy in the caption of Fig. 3. We find that this strategy yields a CAPM alpha of 3.18% per quarter (t-statistic = 5.11) and a Fama and French (2015) five-factor alpha of 1.93% per quarter (t-statistic = 3.71). This timing ability is remarkable, given that the forecast revision is free of look-ahead bias and readily available in real-time. Thus, the results from this forecasting exercise also contribute to the burgeoning field of factor timing and smart beta investments.

4. Exploring the mechanism

In this section, we empirically assess the source of anomaly predictability by investigating expectation errors and firm activities. We first study a few misperception proxies including long-term earnings growth forecast errors, and then financial and real corporate activities, followed by a further check on the portfolios directly sorted on various financial constraint indices. Lastly, we attempt to reconcile the apparent consensus forecast underreaction with stock price overreaction.

4.1. The stronger impact on financially constrained firms

We have argued that IPG forecast revisions could have stronger effects on financially constrained firms. Since the short (long) legs of the anomalies in Panel A (Panel B) in Table 1 are more financially constrained, IPG forecast revisions can predict the anomalies in Panel A (Panel B) with a positive (negative) sign. In this section, we discuss the potential theoretical underpinnings for the stronger impact of IPG forecast revisions on financially constrained firms. In the following sections, we present a further empirical analysis of the mechanisms.

The underlying mechanism is similar to that in the theoretical analysis of Deng (2023) and Gulen et al. (2023). Their models provide the closest theoretical framework for our empirical analysis. Figure 6 of Deng (2023) shows that the interaction between financial frictions and extrapolative expectations results in stronger responses to productivity shocks among financially constrained firms as the feedback from the financial market affects investment and financing decisions through the cost of capital. In addition, Gulen et al. (2023) imply that firms facing more financial frictions should experience larger fluctuations in response to shocks in perceived credit market sentiment. Readers can refer to these models for details. Below we provide a sketch of their key arguments.

Intuitively, after favorable shocks such as upward IPG forecast revisions, extrapolative agents excessively revise upward their expectations of aggregate productivity and become overoptimistic. Firms invest and borrow more. A lower perceived default probability due to optimistic productivity perception improves financing conditions, further increasing investment and borrowing. This effect is particularly strong for financially constrained firms as they are more sensitive to external financing. The key is that extrapolative belief after favorable shocks could further relax the financial constraints of these constrained firms. For unconstrained firms, excessive optimism does not have this effect since they are already investing at a low financing cost. Thus, although all firms improve during upward forecast revisions, financially constrained firms benefit the most due to the additional effects of relaxed financing conditions and decreased cost of capital. This further increases firm investments, excessively inflating the current stock price.

[13] Since many anomalies are mostly driven by small firms and firm size is also related to financial constraints, one might be concerned that our results are driven by small firms. To alleviate such concern, in untabulated analysis, we show that our results are robust after controlling for size. In particular, we first sort stocks into quintiles according to their size (market capitalization), and then within each size quintile, we further divide stocks into quintiles based on the anomaly variable. We then take the average value-weighted excess returns for each anomaly quintile across size quintiles and form long-short anomaly portfolios based on extreme anomaly quintiles. We reach similar conclusion when using these size-adjusted anomalies.

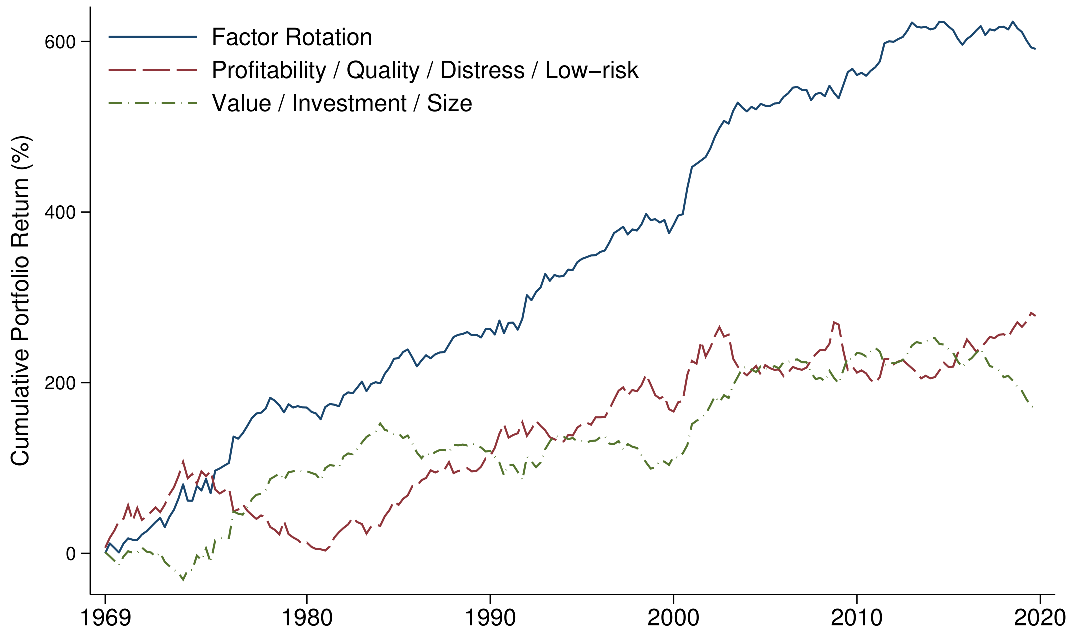

Fig. 3. Rotation strategy performance. This figure compares the performance of the factor rotation strategy with the underlying anomalies from 1969Q1 to 2019Q4. Quarterly CAPM alpha, quarterly Fama and French (2015) five-factor alpha, and annual Sharpe ratio (SR) are displayed in brackets, with Newey and West (1987) eight-lag adjusted t-statistics in parentheses. The solid line plots the cumulative excess returns to the factor rotation strategy [CAPM alpha = 3.18% (t-statistic = 5.11); FF5 alpha = 1.93% (t-statistic = 3.71); SR = 0.71], which invests in the equal combination of anomalies with more financially constrained short legs (ROA, ROE, OP, Quality, FProb, O-Score, TV, and IVOL) following upward revisions in expectations of industrial production growth, and the equal combination of anomalies with more financially constrained long legs (BM, LTR, IA, and SIZE) following downward revisions in expectations of industrial production growth. The dashed line plots the cumulative average returns on anomalies with more financially constrained short legs [CAPM alpha = 2.42% (t-statistic = 3.68); FF5 alpha = 1.27% (t-statistic = 3.12); SR = 0.29]. The dash-dotted line plots the cumulative average returns on anomalies with more financially constrained long legs [CAPM alpha = 0.67% (t-statistic = 0.97); FF5 alpha = –0.23% (t-statistic = –0.85); SR = 0.22].

Eventually, the price reverses when realized productivity falls short of the initially optimistic expectations in subsequent periods.

Numerous studies also show that financially constrained firms are more sensitive to credit conditions (López-Salido et al., 2017; Campello and Chen, 2010; Greenwood and Hanson, 2013). This suggests that when investors revise upward their expectations of aggregate productivity, there is more improvement in the fundamentals of financially constrained firms, and this greater improvement could be further extrapolated into expectations of firm earnings, leading to much higher earnings expectations of financially constrained firms. Thus, the interaction between extrapolation and financial frictions generates positive feedback and amplifies overreaction, leading to lower subsequent returns, particularly for constrained firms. The same intuition applies when investors revise their forecasts of aggregate productivity downward. Following adverse shocks, extrapolative investors become overpessimistic, which exacerbates the financial constraints of firms. For unconstrained firms, this pessimism does not significantly affect their financial constraints, and they can still finance investments at low costs. However, for financially constrained firms, this pessimism further intensifies their financial constraints, resulting in additional downward pressure on their stock prices.

Thus, the theoretical insights from Deng (2023) and Gulen et al. (2023) explain how the interaction effects between extrapolative expectations and financial frictions account for the stronger impacts of IPG forecast revisions on financially constrained firms relative to unconstrained firms. Below, we provide a more detailed empirical analysis of the underlying mechanisms.

4.2. Misperception evidence

If expectations are fully rational, forecast errors in firms' long-term earnings growth should be unpredictable. Prior studies (e.g., Bordalo et al., 2019 and Bordalo et al., 2021) find that analysts and managers tend to extrapolate firm earnings. Below, we provide evidence that the expectations of firms' long-term earnings growth are more extrapolative for financially constrained firms (i.e., unprofitable, low-quality, distressed, risky, value, low-investment, and small firms), in the sense that expectations of their long-term earnings growth are too optimistic after periods of upward IPG forecast revisions.

According to the Gordon growth model, long-term expectations of earnings (or dividend) growth can induce economically significant mispricing. Indeed, Da and Warachka (2011) and Copeland et al. (2004) find that stock returns are sensitive to the misperception in long-term (rather than short-term) analyst forecasts. Additionally, Afrouzi et al. (2023) find, using laboratory experiments, that individuals rely too much on recent observations in forecasting the long-run mean of the process, and this overreaction bias is stronger for longer forecast horizons. Consequently, we examine the predictable pattern for long-term forecasts.

We obtain mean analysts' forecasts for the long-term earnings growth rate (henceforth LTG) from I/B/E/S. LTG is defined as the "expected annual increase in operating earnings over the company's next full business cycle, a period ranging from three to five years." Following Deng (2023) and Bordalo et al. (2019), we calculate the LTG error as the difference between the realized growth rate and the expected growth rate as follows:

$$LTG\_Error_{t+1} = (EPS_{t+13}/EPS_{t+1})^{1/3} - LTG_{t+1}, \tag{8}$$

where EPS_{t+1} denotes the earnings per share in quarter $t+1$ based on street earnings from the I/B/E/S actuals files. We then aggregate the growth forecast errors for each anomaly portfolio after formation. Therefore, positive (negative) LTG errors indicate excessively pessimistic (optimistic) long-term analyst forecasts.

We then examine how LTG errors comove with the revisions in productivity expectations. Formally, we run the following regression:

$$LTG\_Error_{t+1} = \alpha + \beta Frev\_IPG_t + \epsilon_{t+1}, \tag{9}$$

where LTG_Error_{t+1} represents errors in analyst long-term earnings growth forecasts made at quarter $t+1$ (but realized in the future).

Table 8
Evidence of misperception.
The table reports the estimates of β in the following regression:

$$LTG\_Error_{t+1} = \alpha + \beta Frev\_IPG_t + \epsilon_{t+1},$$

where LTG_Error_{t+1} is errors in analysts' forecasts of long-term earnings growth, and $Frev\_IPG_t$ is the revision in expectations of one-quarter-ahead industrial production growth. LTG_Error_{t+1} is calculated as the difference between realized earnings growth and the LTG forecast, that is, $(EPS_{t+13}/EPS_{t+1})^{1/3} - LTG_{t+1}$. We restrict the calculation of realized LTG to the firms with positive EPS in quarter $t+1$, and aggregate it at the portfolio level using capitalization-weighted sum. $Frev\_IPG_t$ is standardized to have zero mean and unit variance. Results are reported for anomalies with financially constrained short legs in Panel A and financially constrained long legs in Panel B. *Average* is the portfolio that equally combines the anomalies in each panel. LTG forecasts begin from 1982Q4 because of data availability. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

	Long leg (1)	Short leg (2)	Long-Short (3)
Panel A: Short leg more financially constrained			
ROA	−3.23	−6.66	3.43
	(−3.16)	(−3.54)	(1.57)
ROE	−1.87	−10.46	8.60
	(−2.62)	(−2.90)	(2.24)
OP	−2.70	−3.68	0.98
	(−2.94)	(−1.46)	(0.37)
Quality	−2.60	−9.71	7.11
	(−2.79)	(−4.09)	(2.75)
FProb	−3.18	−18.65	15.48
	(−3.27)	(−1.48)	(1.19)
O-Score	−3.97	−6.09	2.12
	(−3.06)	(−3.25)	(0.89)
TV	−2.19	−6.50	4.31
	(−2.81)	(−2.37)	(1.52)
IVOL	−1.91	−7.22	5.31
	(−2.46)	(−3.35)	(2.76)
Average	−2.74	−8.90	6.17
	(−3.46)	(−3.62)	(2.44)
Panel B: Long leg more financially constrained			
BM	−7.91	−1.91	−6.00
	(−3.20)	(−2.43)	(−2.32)
LTR	−7.90	−3.72	−4.18
	(−2.79)	(−2.62)	(−1.33)
IA	−6.73	−4.09	−2.64
	(−2.83)	(−3.15)	(−1.38)
SIZE	−2.94	−2.80	−0.14
	(−2.95)	(−3.75)	(−0.14)
Average	−7.43	−3.65	−3.78
	(−2.80)	(−3.01)	(−1.78)

As the SPF results are typically released in the latter part of each quarter (Bordalo et al., 2020), the SPF results released in quarter t may not be immediately recognized by analysts and fully integrated into their LTG forecasts in quarter t. Analysts may start incorporating the SPF information into their forecasts in quarter $t+1$, and thus we focus on the errors in LTG forecasts made at quarter $t+1$. Table 8 reports the estimation results of the regression. As shown, the LTG errors for profitability, quality, distress, and low-risk anomalies are larger when the IPG expectation is revised upward rather than downward. In contrast, the LTG errors for value, investment, and size anomalies are generally lower when the IPG expectation is revised upward rather than downward, a pattern consistent with the return dynamics in Table 6. These findings support the conjecture that investors are exceptionally optimistic about low-profitability, low-quality, distressed, risky, value, low-investment, and small firms when they expect better macro conditions, leading to excessively optimistic forecasts for these firms. Evidently, the predictability of forecast errors is difficult to reconcile with a fully rational framework but is consistent with mispricing-based explanations featuring biased expectations.[14]

As an additional test, we find consistent return patterns around subsequent earnings announcements when investors recognize their previous expectation errors during these dates (Table A12). Engelberg et al. (2018) find that anomalies tend to perform better during subsequent earnings announcements when news arrives and conclude that anomalies are at least partly driven by biased expectations. In line with this view, Table A12 shows that there are higher (lower) earnings announcement returns for anomalies with more financially constrained short (long) legs following upward IPG forecast revisions.

To summarize, the combined evidence on subsequent earnings forecast errors and earnings announcement returns supports the conjecture that the anomaly predictability of $Frev\_IPG$ is likely due to mispricing.[15] Relatedly, Lochstoer and Tetlock (2020) suggest that objective cash flow news drives anomaly returns. Our findings above indicate that subjective cash flow news can also affect anomaly returns, and the effect may stem from investors' extrapolative expectations.

4.3. Contemporaneous corporate activities

As suggested by Deng (2023), financially constrained firms experience a greater reduction in the bond yield spread and a greater increase in investment, debt, and equity issuance in response to an increase in misperceptions about firm-level future productivity. In this subsection, rather than focusing on the effect of misperceptions on firm-level productivity, we investigate the differential impact of IPG forecast revisions on contemporaneous real activities of firms with different degrees of financial constraints.

We construct the financing and investment variables following the literature (López-Salido et al., 2017; Gulen et al., 2023). We obtain bond yield data from the TRACE dataset and calculate the firm-level yield change as the change in the log bond yield, which is the midpoint of the daily last traded yield (yld_pt) in each quarter across different bonds issued by the firm. Financial variables are taken from Compustat Quarterly. Firm debt growth is defined as the change in the log book debt, which is the sum of long- ($dlttq$) and short-term ($dlcq$) debt. The equity growth rate is defined as the change in the log book equity ($seqq$). Firm investment growth is defined as the change in the log of capital expenditures ($capx$). To capture changes in firm financial constraints, we form a quarterly composite index of changes in the firm financial constraint ($\Delta FC\ \ index$) to fit our data's frequency. Specifically, $\Delta FC\ index$ is calculated as the average z-score of cross-sectional ranks of the change in the quarterly WW index (Whited and Wu, 2006), the change in the quarterly HP index (Hadlock and Pierce, 2010), and the change in the quarterly KZ index (Lamont et al., 2001), as in Section 2.3.[16] For each variable, we first build a firm-level measure and winsorize it each quarter at the 1% and 99% percentiles to reduce the impact of extreme observations. Then we aggregate up to the portfolio level by taking the weighted sum of firm-level value.

First, since the SPF forecasts submitted in quarter t are published during quarter t (Han, 2021), we regress the yield change at the portfolio level on contemporaneous IPG forecast revisions to investigate how macroeconomic perceptions influence financing costs. The

[14] We also analyze the standardized unexpected earnings (SUE) for the next one to three years and find that longer-term forecast errors are more predictable (Table A11). This is consistent with recent studies showing that overreaction is stronger for long-horizon forecasts (Afrouzi et al., 2023; Bordalo et al., 2019).

[15] A potential concern is that revisions in one-quarter-ahead IPG forecasts may not match the horizon of long-term earnings growth forecasts. In Table A4, we find that when using revisions in two-quarter-ahead or three-quarter-ahead IPG forecasts, the predictive power for the anomalies is maintained.

[16] According to Farre-Mensa and Ljungqvist (2016), quarterly/annual adjustments of coefficients are virtually never done in the literature, so we follow common practice and use the original coefficients unadjusted (see Section 2.3 for details). For the quarterly KZ index, we use total assets instead of property, plant, and equipment as the latter contains many extreme values in the quarterly data.

results are reported in Table 9. As shown in Table 9, when investors expect an improvement in future macroeconomic conditions, the low-profitability, low-quality, distressed, risky, value, low-investment, and small firms experience a greater reduction in the bond yield relative to their counterparts. These results hold even though these constrained firms experience greater growth in investment, equity, and debt issuance than unconstrained firms, as we discuss in greater detail later. The results for the change in the bond yield suggest that creditors overreact to perceptions of macroeconomic conditions. In contrast, if only the corporate managers overreact but creditors are rational, then one would expect to see an increase in the bond yield and higher investment when IPG expectations are revised upward, disciplining the excess demand by extrapolative managers (Gulen et al., 2023).

Our overreaction hypothesis also suggests that upward IPG forecast revisions coincide with overpricing in corporate bonds, especially for financially constrained firms, leading to stronger reversals in the corporate bond returns of these firms. To test this idea, we collect WRDS bond return data from the companion website to Dickerson et al. (2023).[17] Our findings, presented in Table A13, suggest that financially constrained firms experience lower subsequent corporate bond returns following upward IPG forecast revisions. This means that the return predictability observed in the cross-section of stock returns also appears in the cross-section of corporate bond returns. Therefore, the combined evidence of contemporaneous bond yield changes and subsequent bond returns indicates that extrapolative expectations make financing costs of constrained firms more sensitive to perceptions of macroeconomic conditions.

Second, we show that firms have consistent financing and investment activities, especially those that are financially constrained. Survey evidence suggests that both investors and firm managers are extrapolative (Bordalo et al., 2018; Gennaioli et al., 2016; Barrero, 2022). On the one hand, in the face of upward revisions in expectations of macroeconomic conditions, managers are optimistic about future earnings growth and may finance their expanding investment needs with debt or equity issuance. On the other hand, investors are also more optimistic about firm earnings growth and require a lower return on corporate bonds. These effects reinforce each other, causing cyclical firm activities and exaggerating mispricing.

The remaining columns of Table 9 present the contemporaneous regression results for financing and investment activities. Column (4) shows that a one-standard-deviation increase in IPG forecast revisions coincides with a 0.57% decrease in the debt growth rate of high ROA firms. Conversely, column (5) shows that a one-standard-deviation increase in IPG forecast revisions is associated with a 0.39% increase in the debt growth rate of low ROA firms. However, the favorable revision in IPG expectations leads to a 0.36% increase in the debt growth rate of high-BM firms and a 0.34% decrease in that of low-BM firms. Consistent with Greenwood and Hanson (2013), the results indicate that financially constrained firms issue more debt during credit booms, and the average credit quality of corporate debt issuers deteriorates.

We also observe similar patterns for the growth rate of long-term debt, equity, and investment. The results for equity financing are also reminiscent of the findings of Warusawitharana and Whited (2016), who show that constrained firms issue more equity in response to misvaluation shocks relative to unconstrained firms. Unconstrained firms are already near the optimal level of investment, and thus their financing and investment activities are less affected. Therefore, the above cross-sectional comparisons show that an upward IPG forecast revision is accompanied by an increase in the growth rate of total debt, long-term debt, equity, and investment, particularly for financially constrained (unprofitable, low-quality, distressed, risky, value, low-investment, and small) firms. Notice that Gennaioli et al. (2016) and Gulen et al. (2023) suggest that managers overinvest following good news of firm-level profitability. Thus, we follow Richardson (2006) and measure overinvestment as the residual of regressing investment on a set of firm characteristics to filter out firms' growth opportunities. The empirical evidence is, albeit a bit weak, consistent with the view that constrained firms overinvest during upward IPG forecast revisions (Table A14).

Next, we turn to a comparison of the directly measured financial constraint changes. As before, we run contemporaneous regressions for the changes in the composite index of financial constraints. The estimation results are presented in columns (16) to (18) of Table 9. As expected, the results indicate that as investors turn optimistic about future macroeconomic productivity, unprofitable firms, distressed firms, value firms, low-investment firms, and small firms experience an excessive loosening of financial constraints, which fuels (relative) overinvestment by corporate managers.

Lastly, although the pattern of corporate activities is consistent with an overinvestment interpretation, it is also possible that firm managers respond to investors' optimism after favorable IPG forecast revisions by issuing overpriced equity and low-quality bonds, consistent with the market timing interpretation. In Table A14, we conduct further tests and find suggestive evidence for this alternative explanation. First, we collect S&P credit ratings from S&P RatingXpress and find that there are more downgrades for constrained firms relative to unconstrained firms three years after upward IPG forecast revisions, suggesting that constrained firms issue more low-quality debt. Second, Warusawitharana and Whited (2016) suggest that when managers maximize long-term shareholder value, firms optimally issue (repurchase) overvalued (undervalued) shares, particularly for constrained firms. We thus follow Da et al. (2022) to calculate net firm trading (i.e., net repurchases) and find that constrained firms buy (sell) stocks during downward (upward) IPG forecast revisions. The observation in Table A14 that constrained firms trade in the right direction of future stock price movements confirms the view that firms could act as arbitrageurs (Ma, 2019). Overall, we find suggestive evidence for both the overinvestment and market timing channels. It is worth noting that the overinvestment channel and the market timing channel are not mutually exclusive; in fact, they may even complement each other. Following favorable shocks, firms may raise more capital through equity or debt issuance and then use the raised capital for investments (López-Salido et al., 2017).

To summarize, the returns of equity market anomalies are accompanied by real corporate activities. When expectations of aggregate productivity are revised upward, financially constrained firms experience a greater increase in external financing and investment, which in turn further reinforces investor beliefs. Eventually, this positive feedback loop inflates current stock prices and lowers subsequent returns, as suggested by Greenwood et al. (2021) and Deng (2023). This mechanism helps explain the predictive power of IPG forecast revisions for anomalies documented in Section 3.

4.4. Time variation in returns to financially constrained stocks

Given the results in the previous sections, a natural question to ask is whether IPG forecast revisions have predictive ability for the long-short portfolios that are directly based on measures of financial constraints. By directly exploring the predictability of returns to financially constrained stocks in this subsection, we hope to mitigate concerns over data mining, such as the selection of anomalies.

Based on the intuition discussed before, we expect the returns to the portfolios that long the financially constrained stocks and short the unconstrained ones to be lower (higher) following upward (downward) IPG forecast revisions. To test this conjecture, we first form portfolios based on the three measures of financial constraints as defined in Section 2.3. Following the convention, at the end of June of each year t, we sort the firms into deciles based on the NYSE points of the financial constraint index in the previous year. Value-weighted portfolio returns are then calculated from July of year t to June of year $t+1$.

[17] The data can be accessed at https://openbondassetpricing.com.

Table 9
Contemporaneous corporate activities.
The table reports estimates of β in the contemporaneous regression

$$Y_t = \alpha + \beta Frev\_IPG_t + \epsilon_t,$$

where the dependent variable Y is the change in log yield ($\Delta Yield$), the change in log debt ($\Delta Debt$), the change in log long-term debt ($\Delta LTDebt$), the change in log equity ($\Delta Equity$), the change in log investment (ΔInv), and the change in the quarterly financial constraint index ($\Delta FC\ index$) aggregated at anomaly portfolio levels (the long leg, the short leg, or the difference). $Frev\_IPG_t$ is the revision in expectations of one-quarter-ahead industrial production growth in quarter t and is standardized to have zero mean and unit variance. $\Delta FC\ index$ is calculated as the average z-score of cross-sectional ranks of the change in the quarterly WW index, the change in the quarterly HP index, and the change in the quarterly KZ index. Panels A and C report results for anomalies with more financially constrained short legs, and Panels B and D report results for anomalies with more financially constrained long legs. *Average* is the portfolio that equally combines the anomalies in each panel. Each variable Y_t is aggregated at the portfolio level by taking the asset-weighted sum of firm-level value. $\Delta Yield$ is constructed using TRACE data and spans from 2003Q4 to 2019Q4; other dependent variables are constructed using Compustat Quarterly, and sample periods depend on data availability. Coefficient estimates are multiplied by 100 to be interpretable as approximate percentage changes. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

Dependent variable	$\Delta Yield$			$\Delta Debt$			$\Delta LTDebt$		
	Long leg (1)	Short leg (2)	Long-Short (3)	Long leg (4)	Short leg (5)	Long-Short (6)	Long leg (7)	Short leg (8)	Long-Short (9)
Panel A: Short leg more financially constrained									
ROA	0.02	−0.89	0.91	−0.57	0.39	−0.96	−1.46	−0.46	−1.00
	(0.31)	(−4.59)	(5.67)	(−1.34)	(0.69)	(−1.32)	(−2.40)	(−0.59)	(−1.28)
ROE	−0.02	−1.34	1.32	−0.71	0.09	−0.81	−0.88	−0.61	−0.27
	(−0.32)	(−3.36)	(3.67)	(−1.44)	(0.16)	(−1.82)	(−1.54)	(−0.72)	(−0.42)
OP	0.03	−0.94	0.97	−0.42	0.26	−0.68	−0.88	−0.49	−0.39
	(0.57)	(−4.02)	(4.73)	(−1.03)	(0.58)	(−1.36)	(−1.76)	(−0.72)	(−0.59)
Quality	0.05	−1.26	1.31	−0.38	0.18	−0.56	−0.89	0.96	−1.85
	(0.74)	(−3.28)	(3.67)	(−0.88)	(0.52)	(−0.97)	(−1.50)	(1.52)	(−2.10)
FProb	0.09	−1.02	1.12	−0.17	0.08	−0.25	−0.14	0.41	−0.55
	(1.30)	(−5.11)	(5.46)	(−0.38)	(0.22)	(−0.35)	(−0.28)	(0.68)	(−0.71)
O-Score	−0.00	−1.12	1.12	−0.74	0.25	−0.99	−0.40	0.20	−0.60
	(−0.02)	(−5.38)	(6.68)	(−1.43)	(0.62)	(−1.67)	(−0.93)	(0.51)	(−1.23)
TV	0.05	−2.40	2.45	0.08	1.01	−0.93	0.09	0.82	−0.73
	(0.93)	(−4.24)	(4.36)	(0.27)	(1.18)	(−1.10)	(0.27)	(1.42)	(−0.88)
IVOL	0.03	−2.42	2.45	0.26	0.71	−0.45	0.09	0.60	−0.51
	(0.53)	(−4.59)	(4.72)	(0.75)	(1.06)	(−0.70)	(0.30)	(1.02)	(−0.68)
Average	0.03	−1.42	1.45	−0.39	0.45	−0.84	−0.60	0.13	−0.74
	(0.56)	(−4.58)	(5.13)	(−1.39)	(1.06)	(−1.77)	(−1.62)	(0.31)	(−1.49)
Panel B: Long leg more financially constrained									
BM	−0.55	−0.03	−0.52	0.36	−0.34	0.69	1.70	−0.61	2.31
	(−2.48)	(−0.37)	(−2.57)	(0.71)	(−0.61)	(1.55)	(1.34)	(−1.57)	(2.19)
LTR	−0.97	−0.10	−0.87	−0.60	−0.72	0.12	−0.10	−0.78	0.68
	(−2.55)	(−0.99)	(−2.75)	(−1.91)	(−1.57)	(0.21)	(−0.15)	(−1.38)	(0.71)
IA	−0.49	−0.25	−0.23	0.15	0.63	−0.47	0.18	−0.55	0.73
	(−2.93)	(−2.31)	(−1.97)	(0.40)	(1.46)	(−0.78)	(0.44)	(−1.77)	(1.53)
SIZE	−2.11	0.00	−2.11	0.33	−0.46	0.79	0.99	−0.78	1.77
	(−7.20)	(0.05)	(−7.38)	(1.66)	(−1.66)	(2.91)	(2.27)	(−1.51)	(2.58)
Average	−1.03	−0.10	−0.94	0.03	−0.35	0.39	0.65	−0.91	1.56
	(−4.38)	(−1.14)	(−4.83)	(0.13)	(−1.30)	(1.62)	(1.14)	(−1.86)	(1.98)

Dependent variable	$\Delta Equity$			ΔInv			$\Delta FC\ index$		
	Long leg (10)	Short leg (11)	Long-Short (12)	Long leg (13)	Short leg (14)	Long-Short (15)	Long leg (16)	Short leg (17)	Long-Short (18)
Panel C: Short leg more financially constrained									
ROA	0.09	1.06	−0.97	−1.50	2.69	−4.19	1.88	−1.84	3.73
	(0.45)	(1.65)	(−1.77)	(−0.54)	(1.08)	(−2.56)	(1.92)	(−2.01)	(3.06)
ROE	0.51	1.78	−1.27	−1.09	2.85	−3.95	1.97	−3.14	5.11
	(1.05)	(2.40)	(−1.99)	(−0.41)	(1.16)	(−2.39)	(2.26)	(−5.23)	(5.59)
OP	0.16	0.81	−0.64	−0.59	3.52	−4.11	0.74	−0.27	1.01
	(0.74)	(1.55)	(−1.68)	(−0.23)	(1.54)	(−1.69)	(0.78)	(−0.31)	(1.07)
Quality	0.14	1.89	−1.75	−1.99	4.39	−6.39	1.95	−0.98	2.92
	(0.77)	(2.25)	(−2.26)	(−0.68)	(2.42)	(−2.77)	(2.12)	(−1.34)	(3.30)
FProb	0.11	2.33	−2.23	−2.66	3.63	−6.29	2.00	−1.27	3.28
	(0.50)	(2.08)	(−2.14)	(−1.07)	(1.37)	(−2.82)	(1.74)	(−1.70)	(3.16)
O-Score	0.33	1.47	−1.14	−1.38	3.36	−4.75	0.58	−0.99	1.57
	(1.63)	(3.13)	(−3.36)	(−0.57)	(1.56)	(−1.68)	(0.63)	(−2.15)	(1.64)
TV	0.10	1.16	−1.06	−1.75	3.61	−5.36	0.88	−0.93	1.81
	(0.43)	(1.53)	(−1.77)	(−0.75)	(1.42)	(−3.32)	(0.77)	(−1.31)	(1.34)
IVOL	0.20	1.33	−1.13	−0.88	4.10	−4.98	1.64	−1.67	3.31
	(0.90)	(1.64)	(−1.75)	(−0.37)	(1.56)	(−3.39)	(1.44)	(−2.54)	(2.58)
Average	0.19	1.37	−1.18	−1.48	3.52	−5.00	1.44	−1.39	2.83
	(0.87)	(2.01)	(−2.20)	(−0.61)	(1.75)	(−4.42)	(1.62)	(−2.88)	(3.41)

(*continued on next page*)

It is worth noting that whether financially constrained firms earn higher returns is subject to debate in the literature. On the one hand, Lamont et al. (2001) study the KZ index and find that financially constrained firms earn lower returns than less constrained ones. On the other hand, Whited and Wu (2006) find that firms with a higher WW index earn higher returns than firms with a lower WW index. The summary statistics in Table 10 Panel A confirm the mixed evidence on the relationship between financial constraints and returns. As shown in Panel A, the WW index and HP index deliver positive Fama and French (2015) five-factor alphas, while the KZ index earns negative Fama and French (2015) five-factor alphas during the same sample period.

Table 9 (*continued*).

Panel D: Long leg more financially constrained									
BM	1.44	0.41	1.03	3.30	−0.40	3.70	−0.75	3.63	−4.38
	(2.38)	(1.31)	(2.34)	(1.10)	(−0.16)	(2.21)	(−0.92)	(4.40)	(−3.86)
LTR	0.94	0.33	0.61	2.07	2.04	0.03	−0.58	2.76	−3.34
	(1.52)	(0.90)	(1.83)	(1.01)	(0.90)	(0.02)	(−0.72)	(3.20)	(−3.81)
IA	0.94	0.53	0.41	1.09	0.79	0.30	−1.36	0.74	−2.09
	(2.09)	(1.29)	(1.25)	(0.53)	(0.37)	(0.22)	(−1.14)	(1.03)	(−1.40)
SIZE	0.70	0.45	0.25	2.19	−0.78	2.98	−2.75	0.82	−3.57
	(1.51)	(1.10)	(1.07)	(1.26)	(−0.34)	(2.78)	(−5.49)	(0.86)	(−3.07)
Average	0.96	0.42	0.54	2.16	0.41	1.75	−1.36	1.98	−3.34
	(1.88)	(1.22)	(2.19)	(1.03)	(0.19)	(1.77)	(−2.41)	(3.03)	(−4.66)

Table 10
Returns to financial constraints and macro forecast revisions.
The table reports the unconditional and conditional performance of anomalies formed on financial constraint indices. Panel A reports quarterly excess returns, CAPM alphas, and Fama and French (2015) five-factor alphas of these anomalies in percentages. Panel B reports average excess returns of anomalies formed on financial constraint indices following upward and downward revisions in expectations of industrial production growth. The average returns following upward and downward forecast revisions are estimates of a_U and a_D in the regression

$$R_{t+1} = a_U \cdot \mathbf{1}_{U,t} + a_D \cdot \mathbf{1}_{D,t} + \epsilon_{t+1},$$

where $\mathbf{1}_{U,t}$ and $\mathbf{1}_{D,t}$ are indicators for quarters with upward and downward revisions in expectations of one-quarter-ahead industrial production growth, and R_{t+1} is the excess return on the long leg, the short leg, or the difference. Panel C reports the average CAPM-adjusted returns for anomalies following upward and downward revisions in expectations of industrial production growth. The average CAPM-adjusted returns following upward and downward forecast revisions are estimates of a_U and a_D in the regression

$$R_{t+1} = a_U \cdot \mathbf{1}_{U,t} + a_D \cdot \mathbf{1}_{D,t} + b \cdot Mktrf_{t+1} + \epsilon_{t+1},$$

where $\mathbf{1}_{U,t}$ and $\mathbf{1}_{D,t}$ are indicators for quarters with upward and downward revisions in expectations of one-quarter-ahead industrial production growth, $Mktrf_{t+1}$ is the market factor, and R_{t+1} is the excess return on the long leg, the short leg, or the difference. The portfolio on the WW index (Whited and Wu, 2006) is formed by going long in stocks in the highest WW index decile and shorting those in the lowest WW index decile. The portfolio on the HP index (Hadlock and Pierce, 2010) is formed by going long in stocks in the highest HP index decile and shorting those in the lowest HP index decile. The portfolio on the KZ index (Lamont et al., 2001) is formed by going long in stocks in the highest KZ index decile and shorting those in the lowest KZ index decile. *Average* is the return to the portfolio that equally combines these strategies. The sample period spans from 1969Q1 to 2019Q4. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

Panel A: Unconditional performance

	Excess return			CAPM alpha			FF5 alpha		
Anomaly	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
WW	1.93	1.58	0.35	−0.62	0.17	−0.78	0.59	−0.09	0.67
	(2.22)	(2.91)	(0.49)	(−1.02)	(1.11)	(−1.10)	(2.05)	(−0.92)	(2.10)
HP	1.60	1.58	0.01	−1.04	0.23	−1.27	0.73	−0.30	1.02
	(1.78)	(3.16)	(0.02)	(−1.89)	(1.51)	(−1.91)	(3.04)	(−2.35)	(3.21)
KZ	1.64	1.87	−0.23	−0.59	0.21	−0.80	−0.68	0.36	−1.03
	(2.04)	(2.97)	(−0.36)	(−1.26)	(0.79)	(−1.24)	(−1.42)	(1.53)	(−1.67)
Average	1.72	1.68	0.04	−0.75	0.20	−0.95	0.21	−0.01	0.22
	(2.09)	(3.07)	(0.07)	(−1.54)	(1.34)	(−1.61)	(0.88)	(−0.08)	(0.73)

Panel B: Conditional performance (excess return)

	Long leg			Short leg			Long-Short		
Anomaly	Up	Down	Up–Down	Up	Down	Up–Down	Up	Down	Up–Down
WW	−0.91	4.02	−4.94	0.97	2.03	−1.05	−1.89	2.00	−3.88
	(−0.66)	(3.43)	(−2.71)	(1.31)	(2.60)	(−0.99)	(−1.78)	(2.61)	(−3.30)
HP	−1.04	3.57	−4.61	0.98	2.04	−1.06	−2.02	1.53	−3.55
	(−0.72)	(3.03)	(−2.48)	(1.49)	(2.65)	(−1.03)	(−1.83)	(2.11)	(−2.94)
KZ	−0.74	3.41	−4.16	1.11	2.46	−1.35	−1.86	0.95	−2.81
	(−0.68)	(2.76)	(−2.45)	(1.29)	(2.75)	(−1.10)	(−2.52)	(1.08)	(−2.62)
Average	−0.90	3.67	−4.57	1.02	2.18	−1.15	−1.92	1.49	−3.41
	(−0.73)	(3.16)	(−2.67)	(1.39)	(2.72)	(−1.06)	(−2.39)	(2.14)	(−3.67)

Panel C: Conditional performance (CAPM alpha)

	Long leg			Short leg			Long-Short		
Anomaly	Up	Down	Up–Down	Up	Down	Up–Down	Up	Down	Up–Down
WW	−1.93	0.36	−2.29	0.41	−0.03	0.43	−2.33	0.39	−2.72
	(−2.26)	(0.53)	(−2.30)	(1.93)	(−0.17)	(1.96)	(−2.35)	(0.50)	(−2.44)
HP	−2.09	−0.25	−1.85	0.43	0.06	0.37	−2.53	−0.31	−2.22
	(−2.59)	(−0.39)	(−1.88)	(2.32)	(0.35)	(1.72)	(−2.68)	(−0.41)	(−2.00)
KZ	−1.63	0.19	−1.83	0.44	0.03	0.41	−2.08	0.16	−2.24
	(−2.77)	(0.31)	(−2.22)	(1.42)	(0.10)	(0.99)	(−2.80)	(0.19)	(−2.19)
Average	−1.88	0.10	−1.99	0.43	0.02	0.40	−2.31	0.08	−2.39
	(−3.01)	(0.18)	(−2.69)	(2.43)	(0.13)	(2.14)	(−3.19)	(0.12)	(−2.91)

Table 10 Panel B reports the results of the two-regime analysis for portfolios based on financial constraints. The table reports average excess returns of financial constraint index-sorted portfolios in quarters following upward and downward IPG forecast revisions. For instance, the WW long-short portfolio spread earns –1.89% per quarter following upward IPG forecast revisions. Conversely, the WW long-short portfolio spread earns 2.00% per quarter following downward revisions. The difference of –3.88% between different directions of forecast revisions is not only statistically significant (t-statistic = –3.30) but also economically significant, compared to the average spread of the WW long-short portfolio (0.35%). The remaining results in Panel B based on the HP index and the KZ index are quite similar. When averaged across three measures of financial constraints, the long-short portfolio delivers –1.92% per quarter following upward IPG forecast revisions and 1.49% following downward revisions. In sum, despite the debate over the validity of the indices (Farre-Mensa and Ljungqvist, 2016) and the

Table 11
Aggregate return predictability.
The table reports the estimation results of regressing excess market returns and bank credit conditions on revisions in expectations of aggregate productivity. $Mktrf$ is the quarterly excess stock market return, calculated as the compounded monthly excess stock market return from Kenneth French's website. $Mktb$ is the quarterly excess bond market return, calculated as the compounded monthly excess bond market return from the companion website to Dickerson et al. (2023). $TightCredit$ is the percentage of bank loan officers reporting that they are tightening commercial and industrial lending standards from the Federal Reserve's Senior Loan Office Opinion Survey (SLOOS). $Frev\_IPG$ ($Frev\_UR$) is the revision in consensus forecast of one-quarter-ahead industrial production growth (unemployment rate) from the SPF. Independent variables are standardized to have zero mean and unit variance. The sample spans from 1969Q1 to 2019Q4 for stock market returns, from 2002Q3 to 2019Q4 for corporate bond market returns, and from 1990Q2 to 2019Q4 for the SLOOS survey. Newey–West eight-lag adjusted t-statistics are reported in parentheses.

Dependent variable	$Mktrf_{t+1}$		$Mktb_{t+1}$		$TightCredit_t$		$TightCredit_{t+8}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Frev_IPG$_t$	−1.08		−1.35		−14.00		5.00	
	(−1.35)		(−3.21)		(−4.71)		(1.85)	
Frev_UR$_t$		1.46		1.21		15.94		−7.31
		(2.38)		(3.03)		(5.61)		(−2.92)
Intercept	1.68	1.68	1.50	1.39	6.00	5.38	4.17	4.27
	(2.80)	(2.70)	(3.75)	(4.03)	(1.44)	(1.52)	(0.90)	(0.94)
Obs	203	203	70	70	119	119	119	119

inconsistency in average premia across individual financial constraint indices, the returns to portfolios formed on the three indices are consistently weaker (stronger) following upward (downward) revisions in IPG expectations.

Table A15 takes a further step and shows the relationship between IPG forecast revisions and the contemporaneous corporate financing and investment activities. Consistent with our argument, we find that in response to an upward IPG forecast revision, financially constrained firms experience a greater reduction in bond yields and a greater increase in external financing and investment. Additionally, financially constrained firms have lower subsequent corporate bond returns following upward IPG forecast revisions (Table A16). These findings suggest that the overvaluation in prices is indeed associated with a boost in real financing and investment activities, particularly for financially constrained firms, which corroborates the firm-level results in Deng (2023).

Overall, the takeaway from this subsection is that in addition to many prominent anomalies such as profitability and value anomalies, returns to the financial constraint index-sorted portfolios are also predictable by macroeconomic productivity perceptions.

4.5. Aggregate return and forecast error predictability

The results so far focus on the heterogeneous effects of macroeconomic productivity perceptions on asset prices via financial constraints. In this subsection, we study aggregate return predictability, which not only is of its own interest but also helps evaluate the average impact on the stock market.

Columns (1) and (2), Table 11, present the results of predicting excess stock market returns with macro forecast revisions. An upward revision in IPG expectations predicts lower stock market returns in the subsequent quarter, although the t-statistic is not significant at conventional levels. Moreover, an upward revision in UR expectations predicts higher stock market returns (t-statistic = 2.38). A natural question is whether such predictability would also appear in the corporate bond market. Columns (3) and (4) present results predicting excess corporate bond market returns, which echo those of stock market returns. Classic asset pricing theories suggest that expected risk premia are also driven by the risk aversion coefficient and the amount of market risk. To account for this, we also include proxies for the risk aversion coefficient and the amount of risk in the regression, and the results remain similar (Table A17). These findings support the overreaction hypothesis, indicating that investors overreact to optimistic beliefs about macroeconomic fundamentals and thus subsequently earn lower returns.

Additionally, we investigate the relationship between macro forecast revisions and credit conditions. Columns (5) to (8), Table 11, report the results of regressions that link macro forecast revisions to the credit conditions from the Federal Reserve's Senior Loan Office Opinion Survey, which polls major US banks about credit conditions. $TightCredit$ is defined as the fraction of banks reporting tightening standards among all the respondents. Columns (5) and (6) correspond to results associated with contemporaneous $TightCredit$, and columns (7) and (8) correspond to results associated with two-year-ahead $TightCredit$. As shown, periods of upward revisions in expectations of aggregate productivity are associated with an easing of credit contemporaneously and a tightening of credit two years afterward, a pattern of extrapolation-driven credit cycles (e.g., Greenwood et al., 2021).

More important, we use IPG forecast revisions to predict errors in analysts' aggregate earnings forecasts, providing additional evidence. Table A18 shows that $Frev\_IPG$ negatively predicts subsequent aggregate forecast errors, particularly for longer horizon forecasts. Column (3) shows that the three-year-ahead SUE is 0.58 lower (t-statistic = 1.83) following a one-standard-deviation increase in $Frev\_IPG$. Moreover, column (4) shows that the realized long-term earnings growth rate underperforms expectations more following upward IPG forecast revisions. The stronger results of long-term earnings growth forecast errors are also consistent with Afrouzi et al. (2023), who find in laboratory experiments that individuals rely too much on recent observations in forecasting the long-run mean of the process, and this overreaction bias is stronger for longer forecast horizons. Lastly, in Table A19 we provide additional evidence by examining SPF announcement returns, which capture market reactions to IPG forecast revisions. We find that stock market returns around the SPF announcement date also negatively predict future market returns, suggesting potential overreaction among investors.

In sum, the combined evidence in these tables suggests that the relationship between forecast revisions and subsequent market returns/forecast errors is consistent with overreaction to IPG forecast revisions.

4.6. Reconciling the apparent consensus underreaction with stock price overreaction

Our prior evidence suggests that investors and managers overreact to IPG forecast revisions, and the overreaction-induced mispricing is stronger for financially constrained firms, probably because of the positive feedback effect from relaxation (tightening) of financial constraints following an upward (downward) revision. However, it is well known from Coibion and Gorodnichenko (2015) that consensus forecasts tend to be sticky and may appear to underreact. How can we reconcile this apparent discrepancy? Before we present more detailed evidence on overreaction/extrapolation, let us first review the argument in the literature to establish our background. The existing literature (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Afrouzi et al., 2023) suggests that the positive correlation between (ex ante) forecast revisions and (ex post) forecast errors at the consensus level is because of information rigidities rather than a behavioral bias-induced underreaction.

Indeed, Coibion and Gorodnichenko (2015) argue that the predictability of average ex post forecast errors across agents from ex ante forecast revisions should not be interpreted as a form of irrationality on the part of agents. The stickiness of the consensus forecast is a manifestation of the aggregation process of individual forecasts rather than a behavioral bias-induced underreaction. More important, Bordalo et al. (2020) further examine the relationship between forecast revisions and forecast errors at the individual forecaster level and find pervasive evidence of overreaction to macro news. They present strong evidence that there is an overreaction in individual IPG forecasts, which is consistent with Afrouzi et al. (2023), who show that in laboratory experiments, overreaction is stronger for less persistent processes (e.g., IPG). Similar results are observed among the individual forecasts of GDP growth and real consumption from the SPF.

In sum, existing evidence suggests that the apparent consensus underreaction is probably because of information rigidities, rather than forecasters' underreaction to information, and is a manifestation of the aggregation of individual forecasts. Moreover, overreaction in expectations exists at the *individual* level, as tests of individual beliefs are informative about departures from rationality, but tests of consensus forecasts yield additional information about the role of information frictions (Bordalo et al., 2020).

A crucial question arises regarding how investors and managers interpret the SPF *consensus* forecasts. To address this question, we examine two commonly studied cases of information structure based on the extent to which investors rely on the SPF consensus forecasts.

In the first case, investors completely rely on the SPF consensus forecasts as public signals and adopt SPF consensus forecasts as their own; in this case, there would be an underreaction. Each quarter, the SPF polls professional economists on their forecasts about macroeconomic outcomes in the current and next four quarters, and the results are published around the end of the second month of the quarter (Bordalo et al., 2021). Thus, investors may adopt the SPF consensus forecast as their own. If all investors adopt the SPF consensus forecast as their own, we should observe sluggish reactions in stock prices and a positive correlation between IPG forecast revisions and subsequent market returns. However, the fact that IPG forecast revisions negatively predict subsequent excess market returns in Table 11 is inconsistent with this interpretation. Additionally, Table A19 shows that stock market returns around the SPF announcement date, which capture market reactions to IPG forecast revisions, also negatively, rather than positively, predict future market returns. Relatedly, Roth and Wohlfart (2020) find in a laboratory experiment that when providing the respondents with SPF forecasts, respondents still form their own forecasts of macroeconomic outcomes, extrapolating to expectations about their personal economic circumstances. Hence, the view that all investors adopt SPF consensus forecasts as their own is not supported by the data.

In the second case, similar to Roth and Wohlfart (2020), investors partially rely on the SPF consensus forecast as a public signal for trading while also considering informative private signals. As in Daniel et al. (1998), when public signals confirm private signals, investors' confidence in their private signals rises as self-attribution bias induces overconfidence. Provided that the self-attribution bias is sufficiently large, prices could still overreact to public signals, even in the presence of a conservative public signal. More precisely, we assume that investors receive both a private signal and a public signal. The public signal is conservative, similar to our SPF consensus forecast revisions, possibly due to rigidities in information aggregation. If investors fully adopt the SPF consensus forecast as their own, it would lead to underreaction. However, when coupled with self-attribution bias and overconfidence, overreaction can be restored. Considering a positive public signal, the conservatism in the public signal tends to dampen stock prices below the rational benchmark. Yet, the effect of self-attribution bias is asymmetric; positive private signals tend to receive greater weight compared to negative ones. The asymmetric effect of self-attribution bias can further boost prices. As long as the self-attribution bias outweighs the conservatism in the public signal, stock prices could still appear to overreact to public news. The same intuition applies to a negative public signal. We formalize the above intuition with a simple model in the Appendix, and findings in Tables A17 and A19 corroborate this interpretation.

Therefore, in the second case, managers and investors could exhibit an overreaction to the SPF consensus forecast revisions. Indeed, there is ample direct evidence of managers' and investors' overreaction to macro conditions. Binz et al. (2022) find that managers overreact to GDP estimation errors, leading to a positive short-run investment response and long-run reversal. Gennaioli et al. (2016) document that CFOs' expected earnings growth is lower than the realized earnings growth when past GDP growth is high. Kuchler and Zafar (2019) find evidence of extrapolation in households' expectations of the macro outcomes.[18]

Our evidence on misperception, such as predictable forecast errors and corporate activities, supports the overreaction story in case 2. Our further analysis in Table A20 shows that SPF forecast revisions have a *positive* correlation with investors' and managers' concurrent forecast revisions but a *negative* correlation with their subsequent forecast revisions, consistent with our case 2. Specifically, we regress investors' and managers' forecast revisions on the IPG forecast revisions from the SPF and report the results in Table A20. Panel A reports the results of the Michigan Survey of Consumers (a proxy for retail investors), and Panel B reports the results of the Duke CFO Survey. As shown, the SPF forecast revisions are positively correlated with investors' and managers' concurrent forecast revisions but *negatively* correlated with investors' and managers' subsequent forecast revisions. Therefore, our findings indicate that SPF forecast revisions comove positively with the forecast revisions of retail investors and managers, and negatively predict the subsequent forecast revisions of retail investors and managers, suggesting an overreaction by retail investors and managers.

Furthermore, we examine the evidence of extrapolation in other surveys. Forecast revisions are unpredictable under full-information rational expectations, but they are negatively related to past news if there is an overreaction. As shown in columns (1) to (3) of Table A21, optimistic forecasts of households are typically followed by downward revisions, suggesting an overreaction to the news. Columns (4) and (5) report the results of the Duke CFO Survey, which present similar findings. The results indicate that there is overreaction in the expectations of retail investors and managers even at the consensus level.

Finally, recall from Table A5 that investors' and managers' forecast revisions can also predict anomaly returns. As shown in Table A5, the revisions in expectations of future business conditions or the country's overall economy, as reported by the households in the Michigan Survey of Consumers and managers in the Duke CFO Survey, yield similar results in predicting anomaly returns. Compared to the SPF data, these survey data are available for a shorter period, and thus we use them as robustness checks.

Overall, we find no empirical support for the implications of the first case, while the implications of the second case are consistent with the data. We acknowledge that other mechanisms may reconcile the underreaction in consensus forecasts with the overreaction in stock prices (e.g., Han, 2021), and we leave further investigation to future research. In this study, we focus on the impact of macro forecast revisions on equity market anomalies.

[18] Huang et al. (2023) find that firm managers overextrapolate past earnings in their earnings guidance.

5. Conclusions

Survey evidence indicates that beliefs about macroeconomic conditions are widely shared among investors. By studying the impact of macroeconomic expectations on asset prices, we uncover substantial heterogeneity in the cross-section of stocks. An upward revision in expectations of aggregate productivity is accompanied by an increase in investment and external financing, which inflates current stock prices and lowers subsequent returns, especially for financially constrained firms, including unprofitable, value, risky, and distressed firms. Consequently, revisions in expectations of aggregate productivity positively predict anomalies related to profitability, financial distress, and risks, and negatively predict anomalies related to size, value, and investment.

The broader thrust of our analysis suggests that macroeconomic perceptions generate the cross-sectional financing, investment, and valuation differences, thus driving the *time variation* in these equity market anomalies. However, our results are silent on why these anomalies exist in the first place. An exciting avenue for future research is to investigate whether accounting for different types of financial constraints (Lian and Ma, 2021) would help explain the anomaly returns both unconditionally and conditionally. In addition, most studies tend to focus on financial frictions (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997) or behavioral biases (Bordalo et al., 2018, 2021; Greenwood et al., 2021) separately, with few exceptions such as Deng (2023). In this paper, we highlight the significant role of the interaction between financial frictions and behavioral biases in affecting anomaly returns. Thus, our results indicate that it might be fruitful to further explore the effect of this interaction on anomalies in a quantitative model.

CRediT authorship contribution statement

Wei He: Writing – review & editing, Validation, Investigation, Formal analysis, Conceptualization. **Zhiwei Su:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jianfeng Yu:** Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no relevant financial interests related to the research described in this paper.

Data availability

Replication Package (Original data) (Mendeley Data)

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103952.

References

Afrouzi, H., Kwon, S.Y., Landier, A., Ma, Y., Thesmar, D., 2023. Overreaction in expectations: Evidence and theory. Q. J. Econ. 138, 1713–1764.

Ai, H., Li, J.E., Tong, J., 2021. Equilibrium value and profitability premia. Working Paper.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Finance 61, 259–299.

Antoniou, C., Doukas, J.A., Subrahmanyam, A., 2013. Cognitive dissonance, sentiment, and momentum. J. Finan. Quant. Anal. 48, 245–275.

Asness, C.S., Frazzini, A., Pedersen, L.H., 2019. Quality minus junk. Rev. Account. Stud. 24, 34–112.

Baker, M., Bradley, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. Financ. Anal. J. 67, 40–54.

Baker, M., Stein, J.C., Wurgler, J., 2003. When does the market matter? Stock prices and the investment of equity-dependent firms. Q. J. Econ. 118, 969–1005.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.

Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. J. Finance 59, 1481–1509.

Banz, R., 1981. The relationship between return and market value of common stocks. J. Financ. Econ. 9, 3–18.

Barberis, N., Greenwood, R., Jin, L.J., Shleifer, A., 2015. X-CAPM: An extrapolative capital asset pricing model. J. Financ. Econ. 115, 1–24.

Barberis, N., Greenwood, R., Jin, L.J., Shleifer, A., 2018. Extrapolation and bubbles. J. Financ. Econ. 129, 203–227.

Barberis, N., Jin, L.J., Wang, B., 2021. Prospect theory and stock market anomalies. J. Finance 76, 2639–2687.

Barrero, J.M., 2022. The micro and macro of managerial beliefs. J. Financ. Econ. 143, 640–667.

Bender, J., Sun, X., Thomas, R., Zdorovtsov, V., 2018. The promises and pitfalls of factor timing. J. Portf. Manag. 44, 79–92.

Bernanke, B.S., Gertler, M., 1989. Agency costs, net worth, and business fluctuations. Amer. Econom. Rev. 79, 14–31.

Binz, O., Mayew, W.J., Nallareddy, S., 2022. Firms' response to macroeconomic estimation errors. J. Account. Econ. 73, 101454.

Birru, J., 2018. Day of the week and the cross-section of returns. J. Financ. Econ. 130, 182–214.

Bordalo, P., Gennaioli, N., Ma, Y., Shleifer, A., 2020. Overreaction in macroeconomic expectations. Amer. Econ. Rev. 110, 2748–2782.

Bordalo, P., Gennaioli, N., Porta, R.La., Shleifer, A., 2019. Diagnostic expectations and stock returns. J. Finance 74, 2839–2874.

Bordalo, P., Gennaioli, N., Porta, R.La., Shleifer, A., 2022. Belief overreaction and stock market puzzles. Working Paper.

Bordalo, P., Gennaioli, N., Shleifer, A., 2018. Diagnostic expectations and credit cycles. J. Finance 73, 199–227.

Bordalo, P., Gennaioli, N., Shleifer, A., Terry, S.J., 2021. Real credit cycles. Working Paper.

Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. J. Polit. Econ. 107, 205–251.

Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. J. Finance 63, 2899–2939.

Campello, M., Chen, L., 2010. Are financial constraints priced? Evidence from firm fundamentals and stock returns. J. Money Credit Bank. 42, 1185–1198.

Cassella, S., Chen, Z., Gulen, H., Petkova, R., 2022. Extrapolators at the gate: Market-wide misvaluation and the value premium. Working Paper.

Cassella, S., Gulen, H., 2018. Extrapolation bias and the predictability of stock returns by price-scaled variables. Rev. Financ. Stud. 31, 4345–4397.

Chen, Y., Da, Z., Huang, D., 2022. Short selling efficiency. J. Financ. Econ. 145, 387–408.

Chen, X., He, W., Tao, L., Yu, J., 2023. Attention and underreaction-related anomalies. Manage. Sci. 69, 636–659.

Chen, N.F., Roll, R., Ross, S.A., 1986. Economic forces and the stock market. J. Bus. 59, 383–403.

Cochrane, J.H., 2017. Macro-finance. Rev. Finance 21, 945–985.

Cohen, R.B., Polk, C., Vuolteenaho, T., 2003. The value spread. J. Finance 58, 609–641.

Coibion, O., Gorodnichenko, Y., 2015. Information rigidity and the expectations formation process: A simple framework and new facts. Amer. Econ. Rev. 105, 2644–2678.

Cooper, M., Gulen, H., Ion, M., 2024. The use of asset growth in empirical asset pricing models. J. Financ. Econ. 151, 103746.

Cooper, M.J., Gulen, H., Schill, M.J., 2008. Asset growth and the cross-section of stock returns. J. Finance 63, 1609–1651.

Copeland, T., Dolgoff, A., Moel, A., 2004. The role of expectations in explaining the cross-section of stock returns. Rev. Account. Stud. 9, 149–188.

Da, Z., Dong, X., Wu, K., Zhou, D., 2022. Inside and outside informed trading. Working Paper.

Da, Z., Warachka, M., 2011. The disparity between long-term and short-term forecasted earnings growth. J. Financ. Econ. 100, 424–442.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. J. Finance 53, 1839–1885.

Dasgupta, S., Noe, T.H., Wang, Z., 2011. Where did all the dollars go? The effect of cash flows on capital and asset structure. J. Financ. Quant. Anal. 46, 1259–1294.

De Bondt, W.F.M., Thaler, R., 1985. Does the stock market overreact? J. Finance 40, 793–805.

De la, O.R., Myers, S., 2021. Subjective cash flow and discount rate expectations. J. Finance 76, 1339–1387.

Deng, Y., 2023. Extrapolative expectations, corporate activities, and asset prices. Working Paper.

Dickerson, A., Mueller, P., Robotti, C., 2023. Priced risk in corporate bonds. J. Financ. Econ. 150, 103707.

Dou, W.W., Ji, Y., Wu, W., 2022. The oligopoly lucas tree. Rev. Financ. Stud. 35, 3867–3921.

Engelberg, J., Mclean, R.D., Pontiff, J., 2018. Anomalies and news. J. Finance 73, 1971–2001.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Finance 47, 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. J. Finance 50, 131–155.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.
Farre-Mensa, J., Ljungqvist, A., 2016. Do measures of financial constraints measure financial constraints? Rev. Financ. Stud. 29, 271–308.
Gabaix, X., 2008. Variable rare disasters: A tractable theory of ten puzzles in macro-finance. Amer. Econ. Rev. 98, 64–67.
Gennaioli, N., Ma, Y., Shleifer, A., 2016. Expectations and investment. NBER Macroeconom. Annu. 30, 379–442.
Giglio, S., Xiu, D., Zhang, D., 2021. Test assets and weak factors. Working Paper.
Gourio, F., 2006. Firms heterogeneous sensitivities to the business cycle, and the cross-section of expected returns. Working Paper.
Greenwood, R., Hanson, S.G., 2013. Issuer quality and corporate bond returns. Rev. Financ. Stud. 26, 1483–1525.
Greenwood, R., Hanson, S.G., Jin, L.J., 2021. Reflexivity in credit markets. Working Paper.
Gulen, H., Ion, M., Rossi, S., 2023. Credit cycles and corporate investment. Working Paper.
Hadlock, C.J., Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Rev. Financ. Stud. 23, 1909–1940.
Han, L.J., 2021. Announcements, expectations, and stock returns with asymmetric information. Working Paper.
He, W., Su, Z., Wang, Y., Yu, J., 2023. Time variation in extrapolation and anomalies. Working Paper.
Herskovic, B., Moreira, A., Muir, T., 2019. Hedging risk factors. Working Paper.
Hoberg, G., Maksimovic, V., 2015. Redefining financial constraints: A text-based analysis. Rev. Financ. Stud. 28, 1312–1352.
Hou, K., Loh, R.K., 2016. Have we solved the idiosyncratic volatility puzzle? J. Financ. Econ. 121, 167–194.
Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Rev. Financ. Stud. 28, 650–705.
Huang, D., Lei, L.G., Wang, M., Xing, Y., 2023. Managerial extrapolation: Who and when?. Working Paper.
Imrohoroglu, A., Tuzel, S., 2014. Firm-level productivity, risk, and return. Manage. Sci. 60, 2073–2090.
Jiang, G.J., Xu, D., Yao, T., 2009. The information content of idiosyncratic volatility. J. Financ. Quant. Anal. 44, 1–28.
Jin, L.J., Sui, P., 2022. Asset pricing with return extrapolation. J. Financ. Econ. 145, 273–295.
Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. Amer. Econ. Rev. 105, 1177–1216.
Kaplan, S.N., Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? Q. J. Econ. 115, 707–712.
Kiyotaki, N., Moore, J., 1997. Credit cycles. J. Polit. Econ. 105, 211–248.
Kogan, L., Li, J., Zhang, H.H., 2023. Operating hedge and gross profitability premium. J. Finance 78, 3387–3422.
Kuchler, T., Zafar, B., 2019. Personal experiences and expectations about aggregate outcomes. J. Finance 74, 2491–2542.
Lakonishok, J., Shleifer, A., Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. J. Finance 49, 1541–1578.
Lamont, O., Polk, C., Saa-Requejo, J., 2001. Financial constraints and stock returns. Rev. Financ. Stud. 14, 529–554.
Lian, C., Ma, Y., 2021. Anatomy of corporate borrowing constraints. Q. J. Econ. 136, 229–291.
Lin, H., Paravisini, D., 2013. The effect of financing constraints on risk. Rev. Finance 17, 229–259.
Lochstoer, L.A., Tetlock, P.C., 2020. What drives anomaly returns? J. Finance 75, 1417–1455.
López-Salido, D., Stein, J.C., Zakrajšek, E., 2017. Credit-market sentiment and the business cycle. Q. J. Econ. 132, 1373–1426.
Ma, Y., 2019. Nonfinancial firms as cross-market arbitrageurs. J. Finance 74, 3041–3087.
Maio, P., 2014. Another look at the stock return response to monetary policy actions. Rev. Finance 18, 321–371.
Moreira, A., Muir, T., 2017. Volatility-managed portfolios. J. Finance 72, 1611–1644.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Novy-Marx, R., 2013. The other side of value: The gross profitability premium. J. Financ. Econ. 108, 1–28.
Ohlson, J.A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. J. Account. Res. 18, 109–131.
Pflueger, C., Siriwardane, E., Sunderam, A., 2020. Financial market risk perceptions and the macroeconomy. Q. J. Econ. 135, 1443–1491.
Richardson, S., 2006. Over-investment of free cash flow. Rev. Account. Stud. 11, 159–189.
Roth, C., Wohlfart, J., 2020. How do expectations about the macroeconomy affect personal expectations and behavior? Rev. Econ. Stat. 102, 731–748.
Shanken, J., Mark, W.I., 2006. Economic forces and the stock market revisited. J. Empir. Financ. 13, 129–144.
Shen, J., Yu, J., Zhao, S., 2017. Investor sentiment and economic forces. J. Monetary Econ. 86, 1–21.
Stambaugh, R., 1999. Predictive regressions. J. Financ. Econ. 54, 375–421.
Stambaugh, R., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. J. Financ. Econ. 104, 288–302.
Stambaugh, R., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. J. Finance 70, 1903–1948.
Stivers, C., Sun, L., 2010. Cross-sectional return dispersion and time variation in value and momentum premiums. J. Financ. Quant. Anal. 45, 987–1014.
Wachter, J., 2006. A consumption-based model of the term structure of interest rates. J. Financ. Econ. 79, 365–399.
Warusawitharana, M., Whited, T.M., 2016. Equity market misvaluation, financing, and investment. Rev. Finan. Stud. 29, 603–654.
Welch, I., Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. Rev. Financ. Stud. 21, 1455–1508.
Whited, T.M., Wu, G., 2006. Financial constraints risk. Rev. Financ. Stud. 19, 531–559.