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REVIEW

Anomalies and optionability

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Abstract

We document substantial heterogeneity in how option availability relates to anomaly-based long-short returns across different anomaly categories. After adjusting for differences in firm size and liquidity between optionable and non-optionable stocks, momentum and value anomalies are more pronounced for non-optionable stocks, consistent with binding short-sale constraints and information frictions. Investment anomalies, by contrast, are stronger on optionable stocks, in line with theories suggesting that option availability relaxes funding constraints and thereby makes investment-based risk signals more informative. When averaging across all anomaly signals, these opposing effects offset each other, and anomalies are equally strong on optionable and non-optionable stocks.

Keywords Asset pricing · Anomalies · Options

JEL Classification C15 · C31 · C58 · G12

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1 Introduction

In frictionless and arbitrage-free capital markets, options are redundant assets, and their mere existence does not affect the price of the underlying or any other asset. In real-world markets, however, frictions do exist, and it is important to understand how and to what extent they affect prices. In recent years, a large body of work has shown that options can ease short-selling frictions, information frictions, and funding frictions.[1] At the same time, the empirical asset pricing literature has suggested a large number of firm-specific trading signals that generate profitable investment strategies, so-called "anomalies".[2] Many of these strategies have been shown to generate pronounced return spreads primarily on stocks that are difficult to trade: microcaps, very illiquid stocks, and stocks that are difficult or costly to sell short.[3] These findings suggest friction-based rationales for these anomalies.

This paper is the first to provide systematic evidence on how option availability relates to anomaly returns across a broad set of stock anomalies. We investigate whether anomaly-related long-short returns differ in magnitude between stocks with traded options and those without, and—crucially—whether and how this relation varies across different anomaly categories. Our central finding is that the relation between optionability and anomaly returns is highly heterogeneous across anomaly types, with opposing effects that largely cancel when averaging across all anomalies.

We begin by documenting a raw difference in anomaly returns between optionable and non-optionable stocks. Between 1996 and 2018, the monthly average anomaly return across 144 anomalies was 0.63% (t-statistic of 8.65) for non-optionable stocks, compared to only 0.34% (t-statistic of 3.69) for optionable stocks. The average difference of 0.29% per month is statistically significant (t-statistic of 3.95).

This result must be interpreted with caution. As shown by Mayhew and Mihov (2004), optionable and non-optionable stocks systematically differ in key characteristics such as size and liquidity. This is consistent with option exchange listing criteria, which include specific requirements related to market capitalization and trading activity.[4] It is therefore crucial to assess whether the observed differences in anomaly returns between optionable and non-optionable stocks are an artifact of the differences in the size and liquidity distributions between the two groups.

To this end, we use a particular bootstrap design that ensures identical size and liquidity distributions across the two groups. Using these size- and liquidity-adjusted samples, we find average anomaly returns of approximately 0.5% per month for both optionable and non-optionable stocks. While these numbers refer to equal-weighted

[1] See Figlewski and Webb (1993); Biais and Hillion (1994); Easley and O'hara, M., Srinivas, P.S., (1998); Cao (1999); Danielsen and Sorescu (2001); Chakravarty et al. (2004); Pan and Poteshman (2006); Roll et al. (2009); Hu (2014); Blanco and Wehrheim (2017); Bernile et al. (2025); Cao et al. (2024).

[2] See Hou et al. (2020), Chen and Zimmermann (2022), and Jensen et al. (2023) for an overview.

[3] See for example the discussions in Hou et al. (2020); Drechsler and Drechsler (2014); Muravyev et al. (2025a).

[4] According to current listing requirements of the CBOE (see https://cdn.cboe.com/resources/regulation/rule_book/C1_Exchange_Rule_Book.pdf), the underlying share price must be above $3. Further, there must be at least 7,000,000 publicly held shares with at least 2,000 unique share holders. Finally, the trading volume of the underlying must exceed 2,400,000 shares over the previous 12 months.

raw returns, the result generalizes to value-weighted and to risk-adjusted returns. While optionability may exert some causal influence on firm size and stock liquidity, this channel is plausibly negligible compared to the reverse causal effect of firm size and liquidity on optionability. In general, however, our empirical design cannot fully account for all determinants of option listing. Consequently, the documented differences in anomaly returns should be interpreted as conditional correlations rather than causal effects of option availability.

The average effect masks rich and economically meaningful heterogeneity across anomaly categories, which is the central contribution of our paper. When keeping size and liquidity fixed, we find that "momentum" and "value" anomalies are significantly more pronounced for non-optionable stocks, hinting at roles for short-selling and information frictions in explaining these anomalies. Conversely, "investment" anomalies are stronger on optionable stocks relative to non-optionables. This finding accords with the literature suggesting that option availability alleviates firms' funding constraints. When aggregating across all anomalies, these opposing effects offset each other, which is why the average effect vanishes after controlling for size and liquidity.

In the case of "momentum," the return difference between optionable and non-optionable stocks even increases slightly when adjusting for size and liquidity, consistent with recent findings by Abhyankar et al. (2024). They argue that "momentum" profits are first and foremost driven by short-selling constraints, which limit investors' ability to bet against overpriced stocks in the short leg of "momentum" portfolios. We indeed find that differences in the short leg returns between optionables and non-optionables drive the results.

For "value," we find that controlling for size and liquidity reduces the difference between optionable and non-optionable anomaly returns, but does not eliminate it. This suggests that frictions play a role in the economic mechanism underlying the value premium, and we discuss potential channels through which this effect may operate.

For anomalies from the "investment" category, we find that anomaly returns are significantly more pronounced on optionable stocks than on non-optionable stocks, when appropriately controlling for size and liquidity. This finding may reflect the impact of funding frictions: Bernile et al. (2025) show that option availability relaxes firms' financing constraints, enabling greater investment. Investments in turn serve as a risk signal: Q-theory see, (Cochrane, 1991; Hou et al., 2015) implies that firms invest less when they face riskier future cash flows, so a higher investment rate reveals lower systematic risk exposure. This channel is likely to work better for firms with milder funding constraints, because financially constrained firms cannot set their investments in accordance with the riskiness of their future cash flows. Thus, "investment" characteristics are plausibly more informative for optionable stocks.

We also examine anomalies in the categories "profitability", "intangibles", and "trading frictions". For anomalies in the latter category, we no longer observe differences in anomaly returns between optionable and non-optionable stocks after controlling for size and liquidity. For "profitability" and "intangibles" anomalies, we find no pronounced differences in anomaly returns, neither before nor after controlling for size and liquidity. These anomalies are highly significant in both groups of stocks, but the differences between optionables and non-optionables are negligible. This suggests that frictions – at least those related to the existence of options – do not play a major role in explaining these anomalies.

Our paper contributes to the extensive literature that investigates the informational content of option market statistics for underlying stock prices. A large body of literature suggests that option trading volume contains predictive information about future stock price movements. For example, Easley and O'hara, M., Srinivas, P.S., (1998) develop an asymmetric information model demonstrating that, after conditioning on trade direction – positive (buying calls or selling puts) versus negative (selling calls or buying puts) – option volume can predict stock price movements. Supporting this, Pan and Poteshman (2006) show that stocks with new option positions exhibiting a low put-call ratio (positive signal) significantly outperform those with a high put-call ratio (negative signal). Roll et al. (2010) are among the first to combine option market data with stock market statistics by introducing the options-to-stock trading volume ratio. They find that this measure tends to rise sharply before earnings announcements, suggesting that some investors use options to trade on private information regarding upcoming events. Building on this, Johnson and So (2012) show that when the direction of option trades is unobserved, the options-to-stock trading volume ratio negatively predicts future stock returns. They argue that investors often use options to circumvent costly short-selling in equity lending markets, and primarily trade options on negative information. Beyond trading volume, a more recent branch of literature provides empirical evidence that other option-based measures such as the option-implied volatility spread and the option-implied volatility smirk also have predictive power for future stock returns see, (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Xing et al., 2010; Conrad et al., 2013; Muravyev et al., 2025b; Cao et al., 2022). Notably, all of these studies focus exclusively on stocks with traded options.

Another strand of the literature compares properties of optionable and non-optionable stocks. This line of research proposes channels by which the existence of options can influence firm fundamentals as well as the informativeness and accuracy of stock prices. These studies thus offer potential economic explanations for our findings. Importantly, none of these papers considers the relation between optionability and stock return anomalies. One exception is the paper by Abhyankar et al. (2024), who focus on 12-month momentum, one of the 144 anomalies that we consider.

The paper proceeds as follows. We describe the dataset used in our study and explain the bootstrap approach used to control for size and liquidity differences between optionable and non-optionable stocks in Sect. 2. The results of the empirical analysis are presented in Sects. 3 and 4, where Sect. 3 discusses the average anomaly and Sect. 4 zooms into individual anomaly types. Section 5 gives a comprehensive overview of the main findings and concludes. An Online Appendix provides additional results.

2 Data and empirical design

2.1 Data

We construct our sample using the standard monthly security file from the Center for Research in Security Prices (CRSP). We include all common stocks (share code 10 or 11) listed on the NYSE, NYSE MKT, and NASDAQ (exchange code 1, 2, and 3). To compute anomaly signals, we supplement CRSP with accounting data from the Compustat annual and quarterly files and analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) summary files.

Following standard practice in the return anomalies literature, we exclude stock-month observations with negative or missing book equity (Davis et al., 2000), as well as financial firms SIC codes 6000 to 6999, see, (Hou et al., 2020).

We identify whether a stock is optionable in a given month using OptionMetrics. A stock is considered optionable if, on the portfolio formation date (the last trading day of the month) or within the preceding 27 calendar days, OptionMetrics records the existence of either a call or put option. We define optionability broadly and impose no restrictions on open interest or pricing quality. The 27-day lookback window accommodates infrequent option trading in less liquid stocks and helps avoid misclassifying temporarily inactive optionable stocks.

Our definition of optionability captures whether an option is, in principle, available for trading, rather than whether it is actively traded in practice. Böll et al. (2025) examine, within the sample of optionable stocks, whether option trading volume interacts with anomaly returns. They find that many anomalies are more pronounced among stocks with high option trading volume. Importantly, however, this finding is not informative about the difference in anomaly returns between optionable and non-optionable stocks. Optionable stocks with low option trading volume are still tradable, but there happens to be little demand for them. In contrast, options on non-optionable stocks may face substantial shadow demand, which cannot be satisfied because such options are not listed.

OptionMetrics coverage begins in January 1996. Given the 27-day window, our sample starts in February 1996 and ends in December 2018. Figure 1 shows the evolution of the number of optionable and non-optionable stocks over time. While the total number of stocks decreases, the number of optionable stocks increases steadily. At the end of our sample period, optionable stocks make up more than two-thirds of the entire cross-section of stocks.

Table 1 presents summary statistics for selected stock and firm characteristics that the asset pricing literature identifies as predictors of expected returns. On average, optionable stocks exhibit higher CAPM betas, market capitalizations, and liquidity (as proxied by narrower bid-ask spreads) than non-optionable stocks. These substantial differences motivate our decision to control for size and liquidity when comparing anomaly returns.

Size and liquidity not only influence option eligibility — through, for example, listing requirements or market-maker incentives, as discussed by Mayhew and Mihov (2004) — but may also be affected by the existence of an option. Options can ease short-selling, funding, and information frictions, thereby increasing liquidity

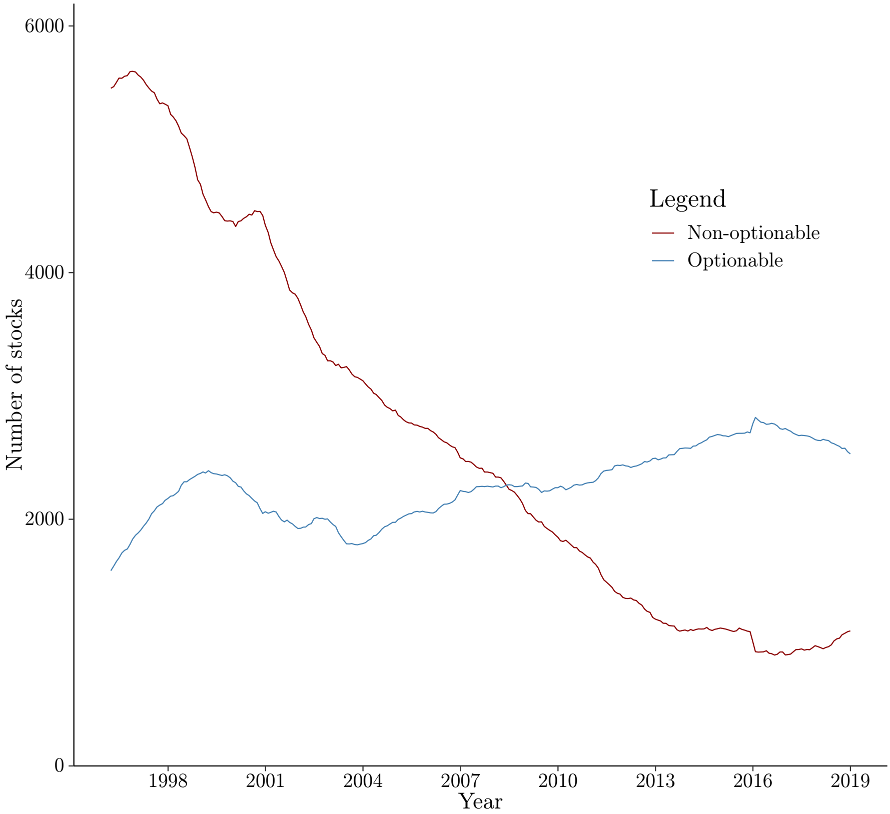

Fig. 1 Number of optionable and non-optionable stocks: This figure shows the number of optionable and non-optionable stocks over our sample period. The red line indicates the number of non-optionable stocks. The blue line indicates the number of optionable stocks. A stock is considered optionable when it has an entry in OptionMetrics at the portfolio formation date or up to 27 days before. When there is no OptionMetrics entry, the stock is considered non-optionable. The sample period is February 1996 to December 2018

and market value. Since our matching procedure equalizes the full distributions of size and liquidity, it may conservatively eliminate both causal and endogenous differences. Disentangling the two channels is beyond the scope of this paper.

We also observe that optionable stocks tend to have lower book-to-market ratios, higher operating profitability, and higher investments, with the latter two scaled by total assets. While these characteristics may drive optionability, they could also reflect more efficient capital allocation and greater access to external finance due to the presence of traded options.

Last, we find that non-optionable stocks tend to have weaker past returns. This finding is in line with Abhyankar et al. (2024), who show that non-optionable stocks are often among the "losers" and remain overvalued due to short-selling constraints. From this perspective, options may facilitate negative information trading and help correct mispricing, resulting in stronger momentum patterns among optionable stocks.

Table 1 Summary statistics: This table shows summary statistics of our data set. Beta is the CAPM market beta, estimated over the past 60 months

Quantile	Beta	Size	BM	Opa	I/A	Mom	Bid-Ask
Panel A: optionable stocks							
2.5%	0.048	69.025	−0.042	−0.170	−0.289	−0.630	0.003
25%	0.537	407.704	0.239	0.098	−0.010	−0.164	0.006
50%	0.902	1150.559	0.440	0.154	0.081	0.068	0.009
75%	1.411	3521.545	0.734	0.222	0.222	0.331	0.013
97.5%	2.716	44340.355	2.037	0.414	1.419	1.581	0.027
Panel B: non-optionable stocks							
2.5%	−0.074	5.550	−0.164	−0.539	−0.423	−0.728	0.003
25%	0.366	30.580	0.412	0.012	−0.052	−0.235	0.009
50%	0.705	76.327	0.737	0.100	0.041	0.022	0.015
75%	1.225	200.021	1.158	0.165	0.145	0.285	0.024
97.5%	2.708	1217.303	4.252	0.354	1.006	1.540	0.064

Size is the one month lagged market equity, BM is the book-to-market ratio, Opa is operating profit scaled by total assets, I/A is annual growth in total assets scaled by one year lagged total assets, Mom is the 12-month momentum, and Bid-Ask is the bid-ask spread, as calculated in Corwin and Schultz (2012). Every month we calculate the cross-sectional 2.5%, 25%, 50%, 75%, and 97.5% quantiles of the respective characteristics and then take the average over our sample period. Panel A shows the values for optionable stocks and Panel B shows the values for non-optionable stocks. A stock is considered optionable if it has an entry in OptionMetrics at the portfolio formation date or up to 27 days before. When there is no OptionMetrics entry, the stock is considered non-optionable. Our sample period is February 1996 to December 2018

2.2 Anomalies

Recent studies have documented a large number of anomaly signals and their associated trading strategy returns see, (Chen and Zimmermann, 2022; Hou et al., 2020; Jensen et al., 2023). Building on the appendix of Hou et al. (2020), we replicate 144 anomalies using one-month holding periods. We follow their categorization into six groups: momentum (9), value (25), trading frictions (25), investment (31), profitability (16), and intangibles (38). Table A14 provides an overview.

As a validation step, we compare our replicated *t*-statistics to those reported in Hou et al. (2020). We compute equally-weighted long-short returns based on decile portfolios, going long the top 10% and short the bottom 10% of stocks. The sample covers all U.S. common stocks, as described in Sect. 2.1, irrespective of optionability. Our sample period generally spans January 1967 to December 2016,[5] consistent with the original study. Figure A1 in the Online Appendix confirms a close match: regressing our replicated *t*-statistics on theirs yields an insignificant intercept, a slope coefficient near one, and an R^2 of 96%.

Our main analysis focuses on the 1996–2018 period, as option data from OptionMetrics are only available from 1996 onward. It is therefore important to first verify that anomaly returns are still present and economically meaningful in this shorter sample, before proceeding with our main analysis. This concern is particularly relevant given that many anomalies were first documented in the early 2000 s, and prior

[5] Some signals are unavailable in early years; we match the starting dates used by Hou et al. (2020).

studies suggest that anomaly returns may weaken after publication see, (Jacobs and Müller, 2020; McLean and Pontiff, 2016; Schwert, 2003).

Panel A of Fig. 2 compares average monthly anomaly returns over the full 1967–2018 period with those from 1996 to 2018. We find no significant difference in average effect sizes between the two periods. Regressing the average returns from the longer period on those from the shorter period yields an insignificant intercept of 0.05% and a slope coefficient of 1.04, which is statistically indistinguishable from one. The solid line shows the fitted value from this regression and lies very close to the dotted 45-degree line. While some anomalies appear weaker in the more recent period (e.g., short-term reversal and various value anomalies), others are more pronounced (e.g., many profitability-related anomalies).

Panel B of Fig. 2 replicates this analysis using *t*-statistics. To account for different sample lengths, we rescale the full-sample *t*-statistics by the square root of the sample size ratio, $\sqrt{23/52} \approx 0.67$. We find that anomalies tend to exhibit slightly higher (adjusted) *t*-statistics over the longer period, with a regression intercept of 0.34 and a slope of 1.14. In light of the results shown in Panel A, this may reflect the higher volatility of anomaly returns during the more recent 23-year period, which includes major market disruptions such as the dot-com crash and the global financial crisis.

2.3 Empirical design

Figure 3 illustrates the distributions of market equity and bid-ask spreads for optionable and non-optionable stocks in our sample. Consistent with Mayhew and Mihov (2004), we find that optionable stocks are systematically larger and exhibit greater liquidity. Given the well-established relation between these characteristics and anomaly returns (Hou et al., 2020), direct comparisons of anomaly returns between these groups require careful adjustment for size and liquidity differences.

To address this, we implement a dependent triple sort on size, liquidity, and the characteristic under consideration and set breakpoints in the size and liquidity sorts that are equal between optionable and non-optionable stocks. Since this inevitably leads to unequal numbers of stocks in each portfolio across the two groups, we have to re-weight observations, which we implement via a bootstrap procedure. Unlike a standard bootstrap that samples uniformly, our method assigns selection probabilities inversely proportional to portfolio counts implied by the double sort on size and liquidity. Intuitively, our procedure assigns small and illiquid optionable stocks relatively higher selection probabilities (because they are rare) than big and liquid optionable stocks, and does the opposite for the group of non-optionable stocks. This ensures matched cross-sectional distributions across groups, enhancing the comparability of subsequent return analyses.

We implement a two-dimensional sorting approach with 100×10 portfolios, balancing granularity against sample retention. While more refined partitions improve

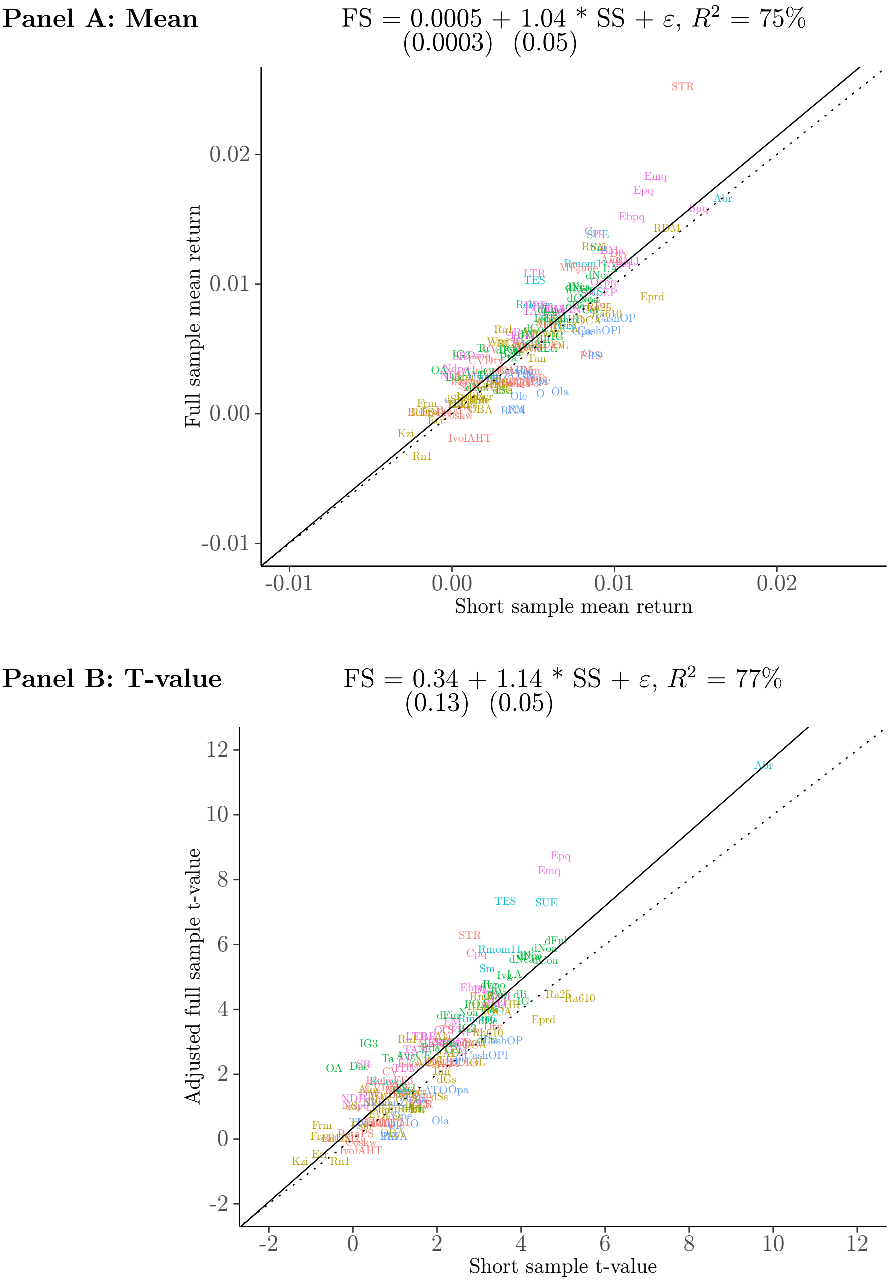

Fig. 2 Long sample versus short sample—Means and t-values: We fit a linear model through anomaly returns and t-values calculated from Feb. 1996 to Dec. 2018 and anomaly returns and t-values calculated from Jan. 1967 to Dec. 2018. The t-values are adjusted for the differences in sample periods. The dashed line indicates the 45-degree line. The x-axis depicts statistics over the short sample. The y-axis depicts statistics over the long sample. Momentum anomalies are shown in light blue, value anomalies in pink, trading frictions anomalies in red, investment anomalies in green, profitability anomalies in dark blue, and intangibles anomalies in dark yellow

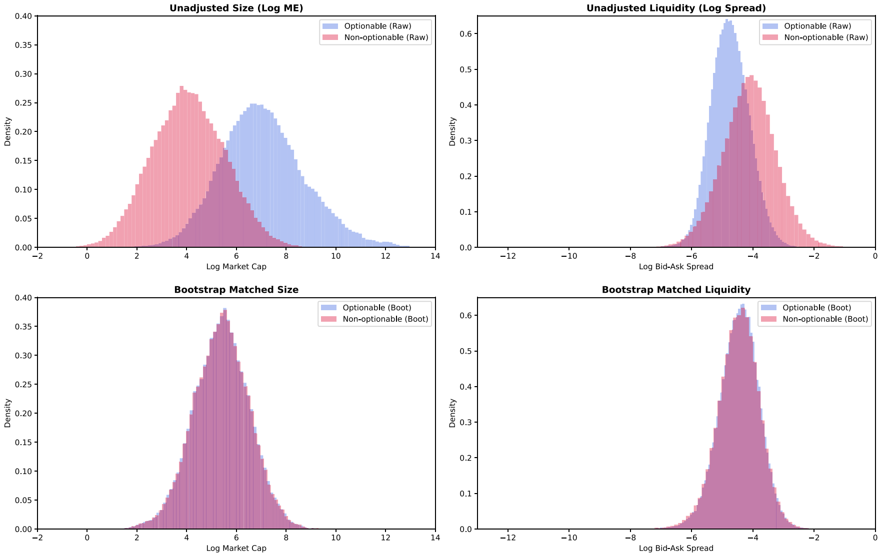

Fig. 3 Unadjusted versus adjusted size and liquidity distributions: This figure displays the weighted probability density functions of log market equity (Size, left column) and log bid-ask spreads (Liquidity, right column) for optionable (blue) and non-optionable (red) stocks over the full sample period from February 1996 to December 2018. The top row displays the unadjusted raw distributions. The bottom row displays the adjusted distributions under our multi-dimensional, overlapping-bin bootstrap matching pipeline

distributional matching, they also increase the likelihood of empty portfolios.[6] To maintain clarity and focus in the main text, further technical details—including breakpoint determination, dropout rates, algorithmic implementation, and robustness diagnostics—are provided in the Online Appendix. Based on 5,000 bootstrap samples, our procedure achieves closely aligned size and liquidity distributions across groups, as illustrated in Fig. 3. Additional bootstraps using uniform sampling probabilities confirm consistency with the original data.

Our bootstrap approach contrasts with traditional 1:1 matching techniques. Related methods in the literature, including those by Abhyankar et al. (2024), Bernile et al. (2025), and Cao et al. (2024), typically impose either restrictive matching criteria or functional form assumptions. For example, Bernile et al. (2025) rely on a linear propensity score model, which may inadequately capture nonlinear relationships between optionability and the characteristics to be matched. In contrast, our method is fully nonparametric and avoids such assumptions. Moreover, unlike 1:1 matching that selects a single counterpart for each treated stock, our bootstrap samples all

[6] This also limits the applicability of the approach to more than two control variables. We also controlled for other criteria beyond size and liquidity, such as stock price and trading volume, and find broadly consistent results. One challenge is that the size and liquidity distributions of optionable and non-optionable stocks are not comparable unless we explicitly control for these variables. This, in turn, implies that returns are not directly comparable between the two groups for those anomalies where the interaction between the anomaly signal and size and liquidity is of first-order importance.

eligible stocks proportionally, mitigating selection bias and improving the representativeness of inference.

A more fundamental limitation of these matching techniques in our setting is that the closest match for a large-cap optionable stock is often a substantially smaller non-optionable stock. As a consequence, the matched samples continue to exhibit markedly different size distributions and, to a lesser extent, liquidity distributions. Moreover, the relatively small number of larger non-optionable firms are repeatedly selected as matches, resulting in their substantial overrepresentation in the matched sample. Our Online Appendix discusses this issue in greater detail and presents additional results.

A limitation that our empirical design shares with all alternative matching designs is that option listing is endogenous. Even if a procedure perfectly equalizes the distributions of size and liquidity across optionable and non-optionable stocks, it cannot fully account for all determinants of option listing. Consequently, the documented differences in anomaly returns should be interpreted as conditional correlations rather than causal effects of option availability.

3 The aggregate anomaly

This section investigates whether return anomalies in the cross-section of U.S. stock returns are more pronounced among optionable or non-optionable stocks. We consider an aggregated anomaly portfolio by forming an equal-weighted portfolio of all individual anomaly portfolios. Specifically, for each of the 5,000 bootstrapped samples, we compute return time series of the long and the short decile portfolios of optionable and non-optionable stocks, separately for each anomaly. We then average these return time series across anomalies, yielding one long and one short portfolio for optionable stocks, and one long and one short portfolio for non-optionable stocks per bootstrapped sample. For each of these time series, we compute the sample mean and the associated *t*-statistic, as well as for the corresponding long-short (i.e., spread) portfolios. All reported statistics in the following tables represent averages across the 5000 bootstrap samples.

Table 2 reports average equal-weighted returns, where equal-weighted here refers to the weighting of stocks within each anomaly portfolio. On non-optionable stocks, the average monthly long-short return is 0.63% per month (*t*-statistic = 8.65), compared to 0.34% (*t*-statistic = 3.69) for optionable stocks. The difference of −0.29% is statistically significant (*t*-statistic = −3.95). At face value, this suggests that anomaly-related strategies are more profitable among stocks without listed options.

The stronger performance of anomaly-related strategies on non-optionable stocks, relative to optionables, is not specific to the weighting scheme. Panel A of Table 3 shows average value-weighted returns on the average across all anomaly portfolios. Value-weighted anomaly returns are on average less pronounced but still significant on optionable and non-optionable stocks. The average long-short return is 0.42% per month (*t*-statistic of 6.12) on non-optionable stocks and 0.25% per month (*t*-statistic of 2.69) on optionable stocks. The difference of −0.17% is statistically significant with a *t*-statistic of −2.34.

Table 2 Equal-weighted returns on anomaly portfolios—all anomalies: For each bootstrap iteration and each month, we average anomaly returns across our entire anomaly universe

	Opt	Nonopt	Δ^{Avg}
Panel A: unadjusted			
Long-short	0.34*** (3.69)	0.63*** (8.65)	−0.29*** (−3.95)
Long	0.91** (2.24)	1.45*** (3.66)	−0.54*** (−2.81)
Short	0.57 (1.25)	0.83* (1.94)	−0.26 (−1.28)
Panel B: adjusted			
Long-short	0.48*** (4.15)	0.45*** (6.08)	0.03 (0.32)
Long	0.88* (1.74)	1.09*** (3.04)	−0.21 (−0.91)
Short	0.40 (0.73)	0.64 (1.63)	−0.24 (−0.94)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. *R* is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Avg} is the difference between *Opt* and *Nonopt*. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996–December 2018

Table 3 Value-weighted returns on anomaly portfolios—all anomalies: For each bootstrap iteration and each month, we average anomaly returns across our entire anomaly universe

	Opt	Nonopt	Δ
Panel A: unadjusted			
Long-short	0.25*** (2.69)	0.42*** (6.12)	−0.17** (−2.34)
Long	0.88*** (2.93)	1.07*** (3.23)	−0.19 (−1.23)
Short	0.64* (1.78)	0.65* (1.80)	−0.02 (−0.10)
Panel B: adjusted			
Long-short	0.33*** (3.20)	0.35*** (4.32)	−0.03 (−0.31)
Long	0.90** (2.16)	1.04*** (3.22)	−0.15 (−0.89)
Short	0.57 (1.24)	0.69* (1.91)	−0.12 (−0.65)

We use 5000 bootstraps, resulting in 5000 aggregated anomaly portfolios. *R* is the average over 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ is the difference between *Opt* and *Nonopt*. Unadjusted depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Adjusted depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel A shows long-short returns, Panel B shows long-leg returns and Panel C shows the short-leg returns. We exclude financial firms and firms with negative book equity before calculating value-weighted anomaly returns. The sample period is February 1996–December 2018

Risk-adjusted returns, reported in Table A1 (equal-weighted) and Table A2 (value-weighted) in the Online Appendix, follow a similar pattern: Long-short differences between CAPM-alphas of average anomaly portfolios are positive and significant on non-optionable and on optionable stocks, but significantly more pronounced within the group of non-optionable stocks.

Our results show that anomaly returns are substantially more pronounced in the group of non-optionable stocks, relative to the group of stocks with traded options. Importantly, this finding provides a stylized fact merely about the correlation between two properties of a stock and should not be interpreted causally. As described earlier, assignment to the two groups is not random, but option exchange listing criteria include minimum size and liquidity bounds. We therefore construct matched samples of optionable and non-optionable stocks following the approach outlined in Sect. 2.3, which effectively controls for size and liquidity, and repeat the above exercise.

When controlling for size and liquidity, the return differential described above disappears completely. Panel B of Table 2 shows that, post-adjustment, the average equal-weighted long-short return is 0.45% per month (t-statistic = 6.08) for non-optionable stocks and 0.48% (t-statistic = 4.15) for optionable stocks, resulting in a statistically and economically insignificant difference of 0.03%. Results are similar for value-weighted returns: Panel B of Table 3 shows that value-weighted long-short returns are equal to 0.35% (t-statistic = 4.32) in the group of non-optionable stocks and 0.33% (t-statistic of 3.20) within optionable stocks. The difference of −0.03% is insignificant. Tables A1 (for equal-weighted returns) and A2 (for value-weighted returns) in the Online Appendix show that controlling for size and liquidity also renders the differences in risk-adjusted anomaly returns between optionable and non-optionable stocks tiny and insignificant.

Overall, our results indicate that non-optionable stocks exhibit "more anomalous" returns than optionable stocks. This association, however, should not be interpreted causally. An analogous statement would be that individuals who frequently watch cartoons have lower mortality rates: failing to control for health status and age would lead to misleading conclusions. Although watching cartoons may causally affect health and, consequently, mortality, such an effect is likely to be of second-order importance relative to the dominant role of age in determining all other variables. Likewise, while optionability may exert some causal influence on firm size and stock liquidity, this channel is plausibly negligible compared to the reverse causal effect of firm size and liquidity on optionability. Taken together, our findings suggest that optionability does not play a first order causal role in determining the strength of *the average* return anomaly.

The aggregate result, while informative, does not by itself shed light on the economic mechanisms underlying anomaly returns. Knowing that optionability has no net effect on the average anomaly is akin to knowing that watching cartoons has no net effect on overall mortality: the aggregate masks potentially rich heterogeneity across components that, once examined, can point to distinct causal channels. To pursue this logic, Sect. 4 turns to the central contribution of the paper and examines heterogeneity across different types of anomalies. Controlling for size and liquidity, we find that certain anomaly categories are significantly more pronounced for optionable stocks, while others are significantly weaker relative to non-optionable stocks. These opposing effects largely offset each other in the aggregate, which is precisely why the aggregate result alone would have led us to understate the economic content of optionability for anomaly returns.[7]

4 Individual anomaly types

4.1 Momentum

Table 4 reports average portfolio returns for the nine momentum anomalies. The fourth column of the table (Δ^{Avg}) reproduces the return differentials from the aggregate anomaly portfolio reported in Table 2. The fifth column (Δ) shows the difference between the momentum-specific return differentials and those of the aggregate portfolio, enabling a direct assessment of how this anomaly category contributes to the overall results presented in Sect. 3.

The average momentum anomaly earns a monthly long-short return of 0.52% (t-statistic = 1.90) on optionable stocks, which is marginally significant. On non-optionable stocks, the return is more than twice as high at 1.06% (t-statistic = 4.19), resulting in a significant difference of −0.54% (t-statistic = 2.18). CAPM-alphas show a similar pattern. Overall, the differences in returns and alphas between optionables and non-optionables are more pronounced for momentum anomalies than for the average anomaly. While we only show equal-weighted returns in this section,

Table 4 Returns on anomaly portfolios—momentum: For each bootstrap iteration and each month, we average anomaly returns across our momentum category

	Opt	Nonopt	Δ^{Mom}	Δ^{Avg}	Δ
Panel A: unadjusted					
Long-short	0.52* (1.90)	1.06*** (4.19)	−0.54** (−2.18)	−0.29*** (−3.95)	−0.25 (−1.22)
Long	1.07*** (2.78)	1.80*** (4.70)	−0.73*** (−4.05)	−0.54*** (−2.81)	−0.19 (−1.54)
Short	0.55 (1.04)	0.74 (1.53)	−0.19 (−0.70)	−0.26 (−1.28)	0.06 (0.60)
Panel B: adjusted					
Long-short	0.66* (1.78)	1.34*** (6.21)	−0.69** (−1.99)	0.03 (0.32)	−0.72*** (−2.61)
Long	1.19** (2.54)	1.60*** (4.00)	−0.41* (−1.81)	−0.21 (−0.91)	−0.20 (−1.23)
Short	0.54 (0.80)	0.26 (0.65)	0.28 (0.72)	−0.24 (−0.94)	0.52*** (3.11)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. *R* is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Mom} is the difference between *Opt* and *Nonopt*, Δ^{Avg} is the same difference for the average anomaly shown in Table 2 and Δ is the difference between Δ^{Mom} and Δ^{Avg}. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996–December 2018

[7] To extend the analogy: if watching cartoons is negatively associated with the risk of a fatal traffic accident, one could hypothesize about a causal effect on commuting intensity. By contrast, a positive relation with the risk of a stroke could hint at a causal effect on cardiopulmonary fitness via reduced physical activity. Neither channel would be visible in the aggregate mortality effect.

value-weighted momentum returns are indeed more pronounced than equal-weighted momentum returns and show qualitatively similar patterns.

When we adjust for differences in size and liquidity among the two groups of stocks, we find that the difference between optionable and non-optionable stocks even increases. In the adjusted sample, the average long-short return is 0.66% (t-statistic = 1.78) on optionable stocks and 1.34% (t-statistic = 6.21) on non-optionable stocks. The return spread increases in magnitude to −0.69% (t-statistic = 1.99). These results indicate that momentum anomalies are not driving the average anomaly pattern documented in Sect. 3. Rather, momentum exhibits a distinct behavior that runs counter to the aggregate results.

To understand this discrepancy, we separately examine the long and short legs. Panel B of Table 4 shows that long momentum portfolios on non-optionable stocks outperform their optionable counterparts by 0.41%. While this spread exceeds the average long-leg difference of 0.21%, the difference is not statistically significant. A similar pattern is observed in the unadjusted sample (Panel A).

The short legs reveal a sharper distinction. In the unadjusted sample, short portfolios of optionable "losers" underperform those of non-optionables by 0.19%, matching the average spread in short legs. After adjusting for size and liquidity, the return on the optionable short portfolio remains largely unchanged (0.55% vs. 0.54%), but the return on the non-optionable short portfolio drops sharply from 0.74% to 0.26%. The adjustment reallocates weight away from small, illiquid non-optionable stocks toward larger, more liquid firms. These results suggest that large, liquid stocks without listed options—when classified as "losers"—experience particularly low returns.

These patterns are consistent with the presence of short-sale constraints. It is well known that certain investors face difficulties in establishing a physical short position in a stock due to limited access to the equity lending market. Constrained investors can instead obtain a negative exposure to a stock by buying put options and/or writing call options on the stock. Although options are in zero net supply, option trades can nonetheless influence stock prices because the counterparty, typically a market maker, hedges the resulting exposure to the underlying risk. Figlewski and Webb (1993) and Danielsen and Sorescu (2001) show that optionable stocks exhibit significantly higher short interest than non-optionable stocks. Thus, options allow a large group of investors to indirectly take part in equity lending markets through option trades with market makers, a strategy referred to as synthetic shorting.[8]

In line with this channel, Abhyankar et al. (2024) highlight the role of options in the decline of momentum returns over the past two decades. They argue that market participants have increasingly used options to trade against overpriced stocks, which arguably comprise a large portion of the "losers" portfolios, i.e. short-legs of momentum strategies. Consistent with our findings, they document stronger momentum among non-optionable stocks and observe that the return gap widens after adjusting for size and liquidity. Their reported extreme raw returns (e.g., –1.45% per month

[8] Garleanu et al. (2008) show that this channel works only imperfectly, since market makers cannot perfectly hedge their long positions without efficient short-selling. As a result, put options can become expensive relative to the implications of put-call parity when the demand for put options or the effective short-selling fees faced by market makers are high.

for non-optionable losers, see Table 3 in their paper) differ *quantitatively* from ours, likely due to differences in sample selection, weighting, and adjustment methods.[9] Qualitatively, however, our results perfectly align with theirs, suggesting that limited short-selling ability in the absence of options may allow overpricing to persist, especially in large, liquid stocks.

To more directly assess the role of short-sale constraints, Table 5 reports cross-sectional regression results for the momentum category, where we augment the baseline specification with shorting fees (*Sf*) as a direct proxy for the cost of short-selling. We note that shorting fee data is only available from May 2002 onward, which shortens the sample to roughly 16 years and reduces statistical power relative to the portfolio sort results. Furthermore, as the cross-sectional regressions use the full cross-section of stocks rather than focusing on the most extreme deciles, the signal is naturally more diluted. Reflecting these limitations, the baseline interaction $Mom \times Opt$ in Column 2 is only marginally significant (-1.04, *t*-statistic of -1.70), though its sign is consistent with the portfolio sort evidence.

Column 3 introduces shorting fees and their interaction with the momentum signal. Two findings stand out. First, shorting fees enter with a strongly significant negative coefficient (-1.62, *t*-statistic of -4.11), indicating that stocks that are more expensive to short earn lower average returns, consistent with the overpricing that arises when short-sale constraints are binding. Second, and more directly relevant, the interaction $Mom \times Sf$ is positive and significant (1.85, *t*-statistic of 2.78), indicating that momentum profits are significantly stronger among stocks with higher shorting fees. This is precisely what one would expect under the short-sale constraint

Table 5 Cross-sectional regressions: momentum category: For every stock we calculate percentile rankings for each firm characteristic within the Momentum category in each month

Dependent variable: returns	(1)	(2)	(3)
Int	0.29 (0.44)	0.75 (1.42)	0.87 (1.23)
Mom	1.38 (2.10)	2.38 (3.21)	3.13 (2.44)
Opt		0.56 (1.34)	0.31 (0.71)
Mom × Opt		−1.04 (−1.70)	−0.79 (−1.22)
Mom × Size		−0.92 (−0.86)	−2.19 (−1.61)
Mom × Liq		−0.00 (−0.00)	−1.29 (−1.28)
Size		−0.73 (−1.04)	−0.46 (−0.57)
Liq		−0.66 (−0.91)	0.42 (0.53)
Sf			−1.62 (−4.11)
Mom × Sf			1.85 (2.78)

We then take the arithmetic mean over all percentile rankings to calculate the stock's aggregate anomaly signal (*Mom*) in each month. In a second step, in each month, we run cross-sectional regressions of returns on the aggregate anomaly signal, the optionability indicator variable (*Opt*), baseline interaction terms, and category-specific secondary controls (Shorting Fees *Sf*). The displayed coefficients are the time-series averages of the monthly estimates. The t-statistics in parentheses are calculated using Fama and MacBeth (1973) standard errors. We exclude financial firms and firms with negative book equity. Given that shorting fee data only starts in May 2002, the sample period for this category runs from June 2002 to December 2018

[9] They analyze 12-month momentum only, use value-weighted returns, include financial firms and stocks with missing or negative book-to-market ratios, and apply a different adjustment procedure, resulting in a non-optionable sample that is larger and more liquid than the optionable one.

channel: when shorting is expensive, the overpriced losers in the short leg of momentum strategies cannot be efficiently arbitraged away, allowing momentum returns to persist. Importantly, upon inclusion of shorting fees and their interaction with the momentum signal, the baseline optionability interaction $Mom \times Opt$ attenuates from -1.04 to -0.79 and loses statistical significance. This pattern is consistent with the interpretation that options mitigate the effective cost of short-selling through synthetic shorting, thereby weakening momentum returns among optionable stocks. While the attenuation is moderate and the residual $Mom \times Opt$ coefficient remains imprecisely estimated, the overall pattern of results is directionally consistent with the short-sale constraint channel and provides more direct support for the proposed mechanism than the portfolio sort evidence alone.

To explore the time dimension of our results, we examine the evolution of category-level anomaly returns for optionable and non-optionable stocks over the sample period. Specifically, we calculate 36-month moving averages of the size- and liquidity-adjusted anomaly returns used throughout our analysis. For each bootstrap iteration, we first compute a separate moving average time series and subsequently average across all 5,000 bootstrap iterations. Figure 4 reports the resulting moving averages for each anomaly category.

Moving-average momentum returns are shown in the upper left graph of Fig. 4. Return differences between optionable and non-optionable stocks are particularly pronounced during the first half of the sample, especially in the early 2000 s. While the gap narrows in later years, momentum returns remain somewhat stronger among non-optionable stocks throughout most of the sample period.

4.2 Value

Table 6 shows returns on investment strategies using average portfolio weights from 25 anomalies in the "value vs. growth" category. In the unadjusted samples, the value premium is far more pronounced among non-optionable stocks. The average value anomaly earns a monthly long-short return of 1.10% (t-statistic = 5.06) for non-optionable stocks, compared to only 0.28% (t-statistic = 0.93) for optionable stocks. The resulting difference of −0.82% is statistically significant (t-statistic = −3.93) and represents the largest unadjusted difference between optionable and non-optionable stocks across anomaly categories.

Importantly, unlike the aggregate anomaly portfolio discussed in Sect. 3, this pronounced return differential does not vanish once differences in size and liquidity are taken into account. The gap shrinks to −0.43%, with the return on optionable stocks increasing slightly to 0.37% (t-statistic = 1.07), while that on non-optionables declines to 0.79% (t-statistic = 3.22). This reflects the well-known pattern that the value premium is stronger among small stocks (see already the early results reported in, Table V, Fama and French (1992)). Even after adjustment, however, the value premium remains considerably larger for non-optionables. Table A4 in the Online Appendix shows a similar, slightly stronger result for CAPM alphas.

Compared to the momentum results discussed in Sect. 4.1, we find that the difference in long leg returns also contributes, even more strongly than the spread in short-leg returns, to the viability of the value anomaly difference between optionables and

Fig. 4 Rolling average anomaly returns of optionable and non-optionable stocks: This figure displays 36-month moving averages of category-level anomaly returns for optionable (blue) and non-optionable (red) stocks. For each bootstrap iteration and month, anomaly returns are first averaged across all signals within a given economic category. We then compute a 36-month moving average separately for each bootstrap time series and average the resulting moving averages across all 5,000 bootstrap iterations. The six panels correspond to the categories Value, Profitability, Momentum, Investment, Intangibles, and Frictions. Returns are adjusted for differences in the size and liquidity distributions between optionable and non-optionable stocks using our bootstrap matching procedure. The sample period is February 1996–December 2018

non-optionables. Value stocks without traded options earn much higher returns than those with options: The spread amounts to −0.83% per month. While size and liquidity adjustments reduce this gap, a difference of nearly half a percentage point remains (−0.47%), compared to −0.21% for the average anomaly.

The pronounced return differential between optionable and non-optionable value stocks is consistent with the notion that options mitigate information frictions, as documented in a broad literature.[10] Informed investors can use options to trade

[10] See Cao (1999); Figlewski and Webb (1993); Hu (2018); Biais and Hillion (1994); Chakravarty et al. (2004); Roll et al. (2009, 2010); Cao et al. (2024); Pan and Poteshman (2006); Hu (2014); Easley and O'hara, M., Srinivas, P.S., (1998); Jennings and Starks (1986); Skinner (1989, 1990).

Table 6 Returns on anomaly portfolios—value: For each bootstrap iteration and each month, we average anomaly returns across our value category

	Opt	Nonopt	Δ^{Val}	Δ^{Avg}	Δ
Panel A: unadjusted					
Long-short	0.28 (0.93)	1.10*** (5.06)	−0.82*** (−3.93)	−0.29*** (−3.95)	−0.54*** (−3.34)
Long	0.92** (2.05)	1.75*** (4.16)	−0.83*** (−3.41)	−0.54*** (−2.81)	−0.29*** (−2.95)
Short	0.65 (1.38)	0.66 (1.53)	−0.01 (−0.04)	−0.26 (−1.28)	0.25*** (2.90)
Panel B: adjusted					
Long-short	0.37 (1.07)	0.79*** (3.22)	−0.43 (−1.58)	0.03 (0.32)	−0.46** (−2.04)
Long	0.86 (1.48)	1.34*** (3.78)	−0.47 (−1.47)	−0.21 (−0.91)	−0.26* (−1.68)
Short	0.50 (0.94)	0.54 (1.28)	−0.05 (−0.19)	−0.24 (−0.94)	0.20* (1.77)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. R is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Val} is the difference between *Opt* and *Nonopt*, Δ^{Avg} is the same difference for the average anomaly shown in Table 2 and Δ is the difference between Δ^{Val} and Δ^{Avg}. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996 to December 2018

against mispricing, be it under- or overvaluation, and Easley and O'hara, M., Srinivas, P.S., (1998) show that call options are often preferred to physical long positions due to their built-in leverage. The ease of trading against mispricing makes optionable stocks more attractive to specialists who have the resources and incentives to engage in intensive information gathering. As a consequence, these stocks may be priced more accurately. Returns on growth stocks (the short leg) are similar across both groups, even after adjustments. This contrasts with the general finding that non-optionables deliver higher returns on both the long and the short legs. For the average anomaly, short leg returns are 0.24% higher among non-optionables, but only 0.05% higher among growth stocks. This result is qualitatively similar to that in Table 4 and could again hint at a channel related to shorting constraints.

To more directly assess the role of information frictions, Table 7 reports cross-sectional regression results for the value category, augmenting the baseline specification with analyst coverage (*Nanalyst*) as a direct proxy for the information environment. We note two general caveats before discussing the results. First, as for the momentum regressions, the cross-sectional framework uses the full stock universe rather than the most extreme deciles, which dilutes the anomaly signal. Second, the baseline interaction $Val \times Opt$ in Column 2 is statistically insignificant (-0.61, t-statistic of -1.36), which we attribute primarily to this dilution effect. Its sign is nonetheless consistent with the portfolio sort evidence, indicating that value anomaly returns are weaker among optionable stocks.

Column 3 introduces analyst coverage and its interaction with the value signal. The results are informative. Analyst coverage itself enters with a strongly significant positive coefficient (2.19, t-statistic of 4.57). More relevant for our purposes, the interaction $Val \times Nanalyst$ is negative and strongly significant (-2.72, t-statistic of -3.81), indicating that value anomaly returns are significantly weaker among

Table 7 Cross-sectional regressions: value category: For every stock we calculate percentile rankings for each firm characteristic within the Value category in each month

Dependent variable: returns	(1)	(2)	(3)
Int	0.20 (0.39)	1.03 (1.99)	1.15 (2.21)
Val	1.85 (3.34)	1.55 (2.07)	1.51 (2.09)
Opt		0.39 (1.53)	0.02 (0.07)
Val × Opt		−0.61 (−1.36)	−0.01 (−0.03)
Val × Size		−1.94 (−1.73)	−0.23 (−0.19)
Val × Liq		2.16 (2.24)	2.61 (2.86)
Size		0.04 (0.05)	−1.66 (−1.86)
Liq		−1.62 (−2.12)	−1.80 (−2.47)
Nanalyst			2.19 (4.57)
Val × Nanalyst			−2.72 (−3.81)

We then take the arithmetic mean over all percentile rankings to calculate the stock's aggregate anomaly signal (*Val*) in each month. In a second step, in each month, we run cross-sectional regressions of returns on the aggregate anomaly signal, the optionability indicator variable (*Opt*), baseline interaction terms, and category-specific secondary controls (Number of Analysts *Nanalyst*). The displayed coefficients are the time-series averages of the monthly estimates. The t-statistics in parentheses are calculated using Fama and MacBeth (1973) standard errors. We exclude financial firms and firms with negative book equity. The sample period is February 1996–December 2018

stocks with better analyst coverage. This is consistent with the information friction channel: when the information environment is richer, fundamental mispricing is less likely to persist, and the return spread between value and growth stocks narrows.

Strikingly, upon inclusion of analyst coverage and its interaction with the value signal, the baseline optionability interaction $Val \times Opt$ collapses from -0.61 to essentially zero (-0.01, *t*-statistic of -0.03). This near-complete attenuation suggests that differences in analyst coverage between optionable and non-optionable stocks account for a substantial part of the optionability differential in value anomaly returns. Since optionable stocks tend to attract greater analyst attention, this pattern is consistent with the view that options are associated with a richer information environment, which in turn reduces the scope for value-based mispricing. Given the weak baseline significance, we interpret these results as suggestive rather than conclusive, but the pattern of attenuation is striking and directionally fully in line with the proposed channel.

Figure 4 reveals interesting time variation in the relation between optionability and value returns. While value returns are generally higher among non-optionable stocks, we find striking patterns in and directly after the Great Financial Crisis (GFC). On the group of optionable stock, we observe strongly negative monthly value anomaly returns during the GFC and a sharp recovery with high positive returns in the three years after the GFC. The value premium exhibits a qualitatively similar pattern on the group of non-optionable stocks, which is, however, less pronounced. This pattern could again hint at lower information and short-sale constraints on the set of optionable stocks, leading to more informed and, in case of a severe crisis like the GFC, more sensitive prices, relative to non-optionables.

In conclusion, value anomalies illustrate that economically meaningful category-specific effects can persist even when aggregate differences between optionable and non-optionable stocks vanish after adjustment, highlighting the importance of accounting for heterogeneity across anomaly classes. The cross-sectional regression evidence further suggests that information frictions, as proxied by analyst coverage, play a meaningful role in driving the value premium differential between optionable and non-optionable stocks.

4.3 Investment

Table 8 reports average returns for 31 anomalies in the "investment" category. In contrast to the momentum, value, and trading frictions categories, we do not observe pronounced return differences between optionable and non-optionable stocks in the unadjusted sample. The average monthly long-short return is 0.39% (t-statistic = 3.95) for optionable stocks and 0.49% (t-statistic = 3.17) for non-optionables, with the difference of −0.09% being statistically insignificant. The same holds for CAPM alphas. After adjusting for differences in size and liquidity, however, a significant reversal emerges. The average investment anomaly earns a monthly long-short return of 0.66% (t-statistic = 3.81) among optionables, compared to 0.22% (t-statistic = 1.34) among non-optionables. The difference of 0.44% is statistically significant (t-statistic = 1.99). The same pattern is evident in CAPM alphas.

Investment anomalies are often explained via a rational channel grounded in Q-theory see, (Cochrane, 1991; Hou et al., 2015). In a frictionless setting, firms with high risk-adjusted values of future cash-flows invest more. As a result, investment behavior is informative about the systematic risks of a firm's cash-flows and, by extension, its expected returns. In the presence of funding frictions, however, a firm's investment policy can only be in line with the underlying systematic risks if the funding constraints do not bind. Funding-constrained firms are forced to invest less, so that their investment rate is not indicative of their systematic risk exposure. In short,

Table 8 Returns on anomaly portfolios—investment: For each bootstrap iteration and each month, we average anomaly returns across our investment category

	Opt	Nonopt	Δ^{Inv}	Δ^{Avg}	Δ
Panel A: unadjusted					
Long-short	0.39*** (3.95)	0.49*** (3.17)	−0.09 (−0.59)	−0.29*** (−3.95)	0.19* (1.65)
Long	0.90** (2.06)	1.30** (2.87)	−0.40* (−1.66)	−0.54*** (−2.81)	0.14* (1.95)
Short	0.51 (1.15)	0.81** (2.08)	−0.31 (−1.54)	−0.26 (−1.28)	−0.05 (−0.75)
Panel B: adjusted					
Long-short	0.66*** (3.81)	0.22 (1.34)	0.44** (1.99)	0.03 (0.32)	0.41** (2.41)
Long	0.85 (1.58)	0.93** (2.24)	−0.08 (−0.30)	−0.21 (−0.91)	0.13 (1.19)
Short	0.19 (0.36)	0.71* (1.92)	−0.52* (−1.84)	−0.24 (−0.94)	−0.28*** (−2.72)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. R is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Inv} is the difference between *Opt* and *Nonopt*, Δ^{Avg} is the same difference for the average anomaly shown in Table 2 and Δ is the difference between Δ^{Inv} and Δ^{Avg}. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996–December 2018 funding constraints distort the informativeness of characteristics in the "investment" category about the firm's risk and cost of capital.

Several papers highlight the connection between optionability and firms' funding conditions. Blanco and Wehrheim (2017) examine whether the existence of traded options is related to a firm's innovation potential. They find that firms with more option trading produce more patents and patent citations per dollar spent on research and development. Bernile et al. (2025) corroborate this finding and highlight the impact of options on the firm's financing constraints. Theory suggests that an improved information environment has positive effects on the firm's ability to access external capital markets see, (Stiglitz and Weiss, 1981; Diamond, 1985). While other firms have to establish a good informational environment through payouts and debt, firms with actively traded options have to rely less on these costly signals. As a consequence, firms with traded options tend to invest both more heavily and more efficiently, as highlighted by Bernile et al. (2025).

Consistent with this logic, we find a more pronounced investment anomaly return among optionable stocks, where funding frictions are presumably less binding. To test the plausibility of this channel, we interpret the long and short portfolios in Table 8 separately. Long portfolios show little difference between optionables and non-optionables. However, short-side returns differ markedly: 0.19% for optionables versus 0.71% for non-optionables. This aligns with the interpretation that high investment firms (short leg) should have low returns due to safe cash flows, but this signal is distorted for firms facing more frictions.

To more directly assess the role of funding frictions, Table 9 reports cross-sectional regression results for the investment category, augmenting the baseline specification with the Altman Z-score Z, see, (Dichev, 1998), a proxy for the probability of default, and the Whited-Wu index WW, see, (Whited and Wu, 2006), a measure for the tightness of external financial constraints. As in the other categories, the cross-sectional framework uses the full stock universe rather than the most extreme deciles, which dilutes the anomaly signal relative to the portfolio sort results. Reflecting this, the baseline interaction $Inv \times Opt$ in Column 2, while significant (1.19, t-statistic of 2.53), is somewhat weaker than the corresponding portfolio sort evidence.

Column 3 introduces the financial constraint proxies and their interactions with the investment signal. In line with Dichev (1998), the Z-score itself enters with a significantly positive coefficient (0.88, t-statistic of 2.01), while the interaction $Inv \times Z$ is significantly negative (-2.08, t-statistic of -2.69). The Whited-Wu index and its interaction with the investment signal are statistically insignificant, suggesting that the Z-score is the more relevant measure of financial constraints in this context, or that the two measures are sufficiently correlated that their effects are difficult to disentangle simultaneously. Importantly, upon inclusion of the financial constraint proxies, the baseline optionability interaction $Inv \times Opt$ attenuates from 1.19 to 0.90 and loses conventional statistical significance (t-statistic of 1.71). This attenuation is consistent with the interpretation that the stronger investment anomaly returns among optionable stocks are at least partly driven by the lower funding constraints of these firms, which makes their investment decisions more informative signals of systematic risk exposure.

Table 9 Cross-sectional regressions: investment category: For every stock we calculate percentile rankings for each firm characteristic within the Investment category in each month

Dependent variable: returns	(1)	(2)	(3)
Int	0.36 (1.02)	1.43 (3.21)	1.47 (1.75)
Inv	1.55 (4.56)	1.13 (1.87)	2.64 (1.89)
Opt		−0.55 (−1.92)	−0.37 (−1.13)
Inv × Opt		1.19 (2.53)	0.90 (1.71)
Inv × Size		−2.56 (−2.85)	−2.37 (−1.50)
Inv × Liq		1.38 (1.83)	0.88 (1.17)
Size		0.21 (0.36)	−0.57 (−0.64)
Liq		−1.30 (−2.50)	−1.00 (−2.01)
Z			0.88 (2.01)
WW			−0.27 (−0.33)
Inv × Z			−2.08 (−2.69)
Inv × WW			−0.77 (−0.48)

We then take the arithmetic mean over all percentile rankings to calculate the stock's aggregate anomaly signal (*Inv*) in each month. In a second step, in each month, we run cross-sectional regressions of returns on the aggregate anomaly signal, the optionability indicator variable (*Opt*), baseline interaction terms, and category-specific secondary controls (Altman *Z*-score and Whited-Wu *WW* index). The displayed coefficients are the time-series averages of the monthly estimates. The t-statistics in parentheses are calculated using Fama and MacBeth (1973) standard errors. We exclude financial firms and firms with negative book equity. The sample period is February 1996–December 2018

Figure 4 indicates that investment-related anomaly returns are consistently stronger among optionable stocks than among non-optionable stocks. This pattern remains relatively stable throughout the sample period, suggesting that the documented effect is not driven by a particular subperiod.

Overall, our findings are consistent with the rational explanation for investment anomalies grounded in Q-theory and highlight the role of funding frictions. The presence of options appears to mitigate these frictions, making investment signals more informative – and return predictability stronger – among optionable stocks. The cross-sectional regression evidence further corroborates this channel: controlling for financial constraints weakens the optionability differential in investment anomaly returns, and the interaction of financial health with the investment signal points to the central role of funding conditions in determining the informativeness of investment-based characteristics.

4.4 Trading frictions

Table 10 reports returns on trading strategies related to 25 anomalies in the category "trading frictions". Similar to the "momentum" and "value-vs. growth" categories, we find a significant difference of −0.30% per month (t-statistic of −2.30) between optionable and non-optionable stocks in the unadjusted sample. When adjusting for size and liquidity, the difference turns positive, with a spread of 0.23% per month, which is statistically insignificant. Overall, this pattern closely resembles that of the average anomaly. The differences between the trading frictions category and the average anomaly in long- and short-leg return differentials are 0.16% (t-statistic =1.59) and −0.04% (t-statistic = −0.34), respectively.

Table 10 Returns on anomaly portfolios—trading frictions: For each bootstrap iteration and each month, we average anomaly returns across our trading friction category

	Opt	Nonopt	Δ^{Trdf}	Δ^{Avg}	Δ
Panel A: unadjusted					
Long-short	0.27 (1.64)	0.57*** (3.20)	−0.30** (−2.30)	−0.29*** (−3.95)	−0.02 (−0.19)
Long	0.81** (2.12)	1.38*** (3.88)	−0.57*** (−3.03	−0.54*** (−2.81)	−0.02 (−0.35)
Short	0.55 (1.11)	0.81* (1.70)	−0.26 (−1.11)	−0.26 (−1.28)	−0.01 (−0.07)
Panel B: adjusted					
Long-short	0.41** (2.34)	0.18 (1.92)	0.23 (0.68)	0.03 (0.32)	0.20 (1.23)
Long	0.81* (1.66)	0.86*** (2.69)	−0.05 (−0.21)	−0.21 (−0.91)	0.16 (1.59)
Short	0.40 (0.66)	0.68 (1.51)	−0.28 (−0.88)	−0.24 (−0.94)	−0.04 (−0.34)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. *R* is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Trdf} is the difference between *Opt* and *Nonopt*, Δ^{Avg} is the same difference for the average anomaly shown in Table 2 and Δ is the difference between Δ^{Trdf} and Δ^{Avg}. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996 to December 2018

The “trading frictions” category includes characteristics that are tightly related to size and liquidity, the properties we control for when adjusting the groups. For example, *MEjune*, defined as a firm’s market equity in June of the previous calendar year, is strongly cross-sectionally correlated with our size measure (market equity in the previous month). In the unadjusted sample, we find a pronounced size effect among non-optionable stocks but none among optionables. After adjusting for size and liquidity, the effect vanishes in both groups. A similar pattern emerges for liquidity-related variables, including the Amihud (2002) measure.

Nonlinearities in the relations between expected returns and many characteristics related to trading frictions may explain the concentration within non-optionable stocks in the unadjusted sample. Return differences between moderately liquid and very liquid stocks are likely minimal, but return differences between moderately liquid and very illiquid stocks can be substantial. Another prominent example of such a non-linearity in expected returns is the *idiosyncratic volatility* anomaly, also a member of this category. Consistent with this, frictions premia tend to be concentrated among stocks more exposed to such frictions (non-optionables).

However, once size and liquidity are accounted for, these return differentials disappear. This suggests that the additional frictions associated with non-optionability do not explain variations in returns beyond what is already captured by size and liquidity. Figure 4 shows no clear or persistent anomaly return difference between adjusted optionable and non-optionable stocks in any subperiod. The differences fluctuate over time and do not reveal a systematic pattern, which is consistent with negligible unconditional return difference on the adjusted samples.

4.5 Profitability and intangibles

Table 11 reports average anomaly returns across 16 profitability-based strategies. We find no economically or statistically meaningful differences between optionable and non-optionable stocks, neither before nor after adjusting for size and liquidity. The profitability premium is robust across both groups: the average anomaly earns a monthly long-short return of 0.60% (t-statistic = 2.83) for optionable stocks and 0.62% (t-statistic = 2.04) for non-optionable stocks. The difference of −0.02% is statistically insignificant. Adjusting for size and liquidity has little impact on these results. The average profitability anomaly earns a monthly long-short return of 0.70% (t-statistic = 2.21) among optionable stocks and 0.83% (t-statistic = 2.93) among non-optionable stocks. The difference of −0.12% remains statistically insignificant.

Table 12 reports average returns across 38 anomaly portfolios related to “intangibles”. Results are similar to those reported for profitability anomalies: The average intangibles anomaly earns a monthly long-short return of 0.24% (t-statistic = 3.55) for optionable stocks and 0.37% (t-statistic = 3.50) for non-optionable stocks. The difference of −0.13% is statistically insignificant. After adjusting for size and liquidity, the return is 0.32% (t-statistic = 2.34) for optionable and 0.21% (t-statistic = 1.92) for non-optionable stocks, yielding a difference of 0.11% which is, again, insignificant.

Consistent with the small unconditional return differences, Fig. 4 shows no strong time-series patterns in anomaly return differences between adjusted optionable and non-optionable stocks. Overall, the evidence suggests that anomalies in the “profitability” and “intangibles” category are less likely to be related to frictions that option markets help to mitigate. They behave similarly to the average anomaly after

Table 11 Returns on anomaly portfolios—profitabilitycapital letter."?> for each bootstrap iteration and each month, we average anomaly returns across our profitability category

	Opt	Nonopt	Δ^{Prof}	Δ^{Avg}	Δ
Panel A: unadjusted					
Long-short	0.60*** (2.83)	0.62** (2.04)	−0.02 (−0.10)	−0.29*** (−3.95)	0.26 (1.25)
Long	0.96** (2.49)	1.38*** (3.92)	−0.42* (−2.42)	−0.54*** (−2.81)	0.12 (1.29)
Short	0.36 (0.68)	0.76 (1.34)	−0.40 (−1.30)	−0.26 (−1.28)	−0.14 (−0.98)
Panel B: adjusted					
Long-short	0.70** (2.21)	0.83*** (2.93)	−0.12 (−0.44)	0.03 (0.32)	−0.16 (−0.67)
Long	0.86* (1.88)	1.17*** (3.54)	−0.31 (−1.36)	−0.21 (−0.91)	−0.10 (−0.89)
Short	0.16 (0.24)	0.34 (0.67)	−0.18 (−0.51)	−0.24 (−0.94)	0.06 (0.32)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. R is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Prof} is the difference between *Opt* and *Nonopt*, Δ^{Avg} is the same difference for the average anomaly shown in Table 2 and Δ is the difference between Δ^{Prof} and Δ^{Avg}. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996 to December 2018

Table 12 Returns on anomaly portfolios—intangibles: For each bootstrap iteration and each month, we average anomaly returns across our intangibles category

	Opt	Nonopt	Δ^{Int}	Δ^{Avg}	Δ
Panel A: unadjusted					
Long-short	0.24*** (3.55)	0.37*** (3.50)	−0.13 (−1.14)	−0.29*** (−3.95)	0.16** (2.32)
Long	0.92** (2.24)	1.37*** (3.26)	−0.46** (−2.18)	−0.54*** (−2.81)	0.08** (1.96)
Short	0.68* (1.65)	1.01*** (2.62)	−0.33* (−1.77)	−0.26 (−1.28)	−0.07 (−1.49)
Panel B: adjusted					
Long-short	0.32** (2.34)	0.21* (1.92)	0.11 (0.68)	0.03 (0.32)	0.08 (0.66)
Long	0.88* (1.72)	1.04*** (2.71)	−0.15 (−0.63)	−0.21 (−0.91)	0.06 (0.77)
Short	0.57 (1.12)	0.83** (2.37)	−0.26 (−1.07)	−0.24 (−0.94)	−0.02 (−0.25)

We use 5000 bootstrap iterations, resulting in 5000 aggregated anomaly portfolios. R is the average over the 5000 time series mean returns. Average t-values are displayed in parentheses. In *Opt* we only use stocks which have an entry in OptionMetrics at the portfolio formation date or up to 27 days before to calculate anomaly returns. In *Nonopt* we only use stocks which have no OptionMetrics entry to calculate anomaly returns. Δ^{Int} is the difference between *Opt* and *Nonopt*, Δ^{Avg} is the same difference for the average anomaly shown in Table 2 and Δ is the difference between Δ^{Int} and Δ^{Avg}. Panel A depicts anomaly returns when we do not adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. Panel B depicts anomaly returns when we adjust for differences in the size and liquidity distributions between optionable and non-optionable stocks. We exclude financial firms and firms with negative book equity before calculating equal-weighted anomaly returns. The sample period is February 1996 to December 2018

adjustment, showing no meaningful return differentials between optionable and non-optionable stocks.

5 Discussion and conclusions

Our empirical analyses show that stock market anomalies are much more pronounced on stocks without traded options, relative to the group of optionable stocks. To the best of our knowledge, our paper is the first to document this stylized empirical fact. Importantly, this difference disappears completely when we adequately account for differences in size and liquidity between the stocks in the two groups. This finding suggests that the opportunity to trade an option on an underlying alone is not indicative of stock prices being more informed or, more generally, stock returns being less "anomalous."

Our findings are not surprising from the perspective of a frictionless arbitrage-free model of the asset market: Under these assumptions, options are redundant as they can be replicated by stocks and bonds. Hence, no differences in anomaly returns between optionable and non-optionable stocks would be expected. However, real markets feature frictions, and options may alleviate some of them. Our investigation can thus potentially be informative about the origins of anomalies.

Abhyankar et al. (2024) show that the classic momentum strategy is much stronger on non-optionable stocks, even after controlling for size and liquidity. While we confirm their finding (and even show that it also holds for other "momentum" anomalies), our findings show that these results do not generalize to other anomalies. Overall, this implies that the average anomaly is likely not driven entirely by short-sale constraints as it is arguably the case for the momentum anomaly.

We find pronounced differences in the returns on some anomaly types: Before adjustment, anomalies are stronger on non-optionable stocks for “momentum”, “value”, and “trading frictions” categories. “Investment”, “profitability”, and “intangibles” anomalies show no significant average differences. After adjusting for size and liquidity, “momentum” and “value” anomalies remain stronger on non-optionable stocks. “Trading friction”, “profitability”, and “intangibles” anomalies show no significant difference between the two groups after adjustment. Investment anomalies become significantly stronger on optionable stocks, relative to non-optionables, post-adjustment.

Our “momentum” results suggest the channel discussed thoroughly by Abhyankar et al. (2024): short-selling frictions limit selling overpriced non-optionable stocks, which are associated with anomalously low returns relative to high “momentum” stocks. This effect is weaker for optionable stocks. Consequently, optionability seems to have a mitigating effect on short-selling constraints.

Importantly, our main result suggests that short-selling constraints are crucial for understanding “momentum” returns, but cannot serve as a “one-for-all explanation” of anomaly returns in general. Instead, information frictions could explain the higher returns of non-optionable value stocks relative to optionable value stocks. We find that the difference in value premia between non-optionables and optionables survives adjusting for size and liquidity and stems primarily from the long legs of the portfolios.

Finally, our findings are in line with a rational explanation of “investment” anomalies. The return spread between low- and high-investment firms is more pronounced for optionable stocks. Evidence from Bernile et al. (2025) suggests that firms with traded options face fewer funding frictions. This plausibly leads to an investment policy which is better aligned with the properties of their future cash-flows. Hence, their investments may be more informative about their cost of capital. In contrast, non-optionable stocks are more likely to be funding-constraint and thus invest until their constraints bind. Our results are thus consistent with the rational explanation of the “investment” anomaly implied by Q-theory.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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