Asset Pricing Anomalies and Option Markets

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Chapter 1

Introduction

1.1 Motivation and Thematic Overview

A central objective of empirical asset pricing is to understand why expected returns differ across stocks. Over the past several decades, researchers have documented that cross-sectional variation in stock returns is systematically related to firm characteristics, including accounting-based measures such as book-to-market equity and operating profitability, as well as market-based characteristics such as past stock returns. The accumulation of these findings has led to what is often described as a "zoo" of return patterns in equity markets (see, e.g., Chen and Zimmermann, 2022; Jensen et al., 2023).

These return patterns are typically identified using either cross-sectional regression methods or portfolio-sorting approaches. In the latter approach, stocks are sorted according to a candidate characteristic, and the returns of firms with high characteristic values are compared with those of firms with low characteristic values, often through a long–short trading strategy that buys stocks in the high-characteristic portfolio and sells stocks in the low-characteristic portfolio. If firms with high and low characteristic values subsequently earn systematically different returns, the resulting return spread is interpreted as evidence of a cross-sectional return pattern associated with that characteristic. Such return patterns are commonly referred to as "anomalies" because many of them are not fully explained by standard asset-pricing models, including benchmark factor models such as the Fama and French (1993) three-factor model.

While many of these anomalies were discovered decades ago, the underlying mechanisms behind them continue to be actively debated in the literature. The literature commonly offers two explanations. First, there may be cross-sectional return differences between portfolios because stocks with high realizations of a certain firm characteristic are inherently riskier than stocks with low realizations of that characteristic and therefore command a risk premium from investors. This explanation is commonly referred to as the risk-based explanation. Alternatively, stocks with high realizations of a certain firm characteristic may exhibit relatively high expected returns because they are underpriced, while stocks with low realizations may exhibit relatively low expected returns because they are overpriced. This explanation is referred to as the mispricing-based explanation.

Recently, a growing strand of the literature has attempted to disentangle these two explanations. For example, Frey (2023) link anomalies to biased expectations and thus to mispricing by analyzing whether firm characteristics are cross-sectionally correlated with future earnings forecast revisions. Bali et al. (2023) link anomalies to mispricing by examining whether their returns deviate from the returns implied by an Instrumented Principal Component (IPCA) factor model. Chen et al. (2023) categorize anomalies into risk- and mispricing-based categories based on the statements of the original authors.

This dissertation contributes to this ongoing debate about the underlying mechanisms of asset pricing anomalies by analyzing anomalies through the lens of the options market. A prominent strand of the literature documents that the options market constitutes an attractive venue for informed investors seeking exposure to the underlying securities. For example, Chakravarty et al. (2004) and Easley et al. (1998) argue that it can be optimal for informed investors to trade in the options market rather than in the equity market because the leverage embedded in options allows investors to obtain large exposures while committing relatively little capital. Consistent with this view, a growing body of evidence shows that option market characteristics such as option prices and trading volume contain information about the future price of the underlying stock (see, e.g., Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Ge et al., 2016; Hu, 2014; Johnson and So, 2012; Muravyev et al., 2025b; Pan and Poteshman, 2006; Roll et al., 2010). Taken together, this evidence suggests that the options market provides a channel through which information about the underlying security is reflected in market prices.

Against this background, relating option market characteristics to firm characteristics provides a promising approach to studying the underlying nature of anomalies. If anomalies capture mispricing or reflect compensation for risk, these mechanisms may also be reflected in the behavior of investors in the options market. Moreover, the availability of listed equity options can alleviate several market frictions that may affect anomaly returns, including short-selling constraints, funding constraints, and information frictions. For example, Danielsen and Sorescu (2001) show that the introduction of options provides a means for investors to take short positions, thereby alleviating short-selling constraints in the underlying equity market. Cao et al. (2024) document that stocks with listed options exhibit more informative prices, while Bernile et al. (2025) provide evidence that the presence of options is associated with fewer funding constraints. Despite these insights, the implications of option listing for anomaly returns remain largely unexplored. While a small number of studies examine specific anomalies, the literature has yet to provide a systematic assessment of how the presence of options affects the returns of a broad set of anomaly strategies. For example, Abhyankar et al. (2024) study the momentum anomaly and compare its returns between optionable and non-optionable stocks. They find that the momentum anomaly is weaker among optionable stocks, consistent with an interpretation based on binding short-selling constraints, and therefore supportive of a mispricing-based explanation.

This dissertation extends this line of inquiry by systematically comparing anomaly returns between stocks with traded options and stocks without traded options across a wide range of anomalies. The average anomaly generates significant returns on both groups of stocks, and differences in average returns between optionable and non-optionable stocks can largely be explained by differences in firm size and liquidity. However, there is substantial heterogeneity across anomaly categories. In particular, value- and momentum-related anomalies tend to remain stronger among non-optionable stocks, consistent with the importance of short-selling and information frictions, whereas investment-related anomalies are more pronounced among optionable stocks, consistent with options mitigating funding constraints and enhancing the information content of firms' investment decisions. These findings suggest that optionability affects anomaly returns through multiple economically distinct mechanisms rather than a single common channel.

Beyond the mere presence of options, option prices can also reveal how traders position themselves with respect to anomaly signals. Informed investors seeking to exploit stock mispricing may use option contracts to obtain directional exposure to anomaly portfolios. For instance, investors expecting stocks in an anomaly's long portfolio to outperform may gain such exposure by purchasing call options or selling put options, while negative views on stocks in an anomaly's short portfolio may be expressed through put purchases or call writing. Alternatively, investors anticipating elevated risk associated with certain anomaly portfolios may use options for hedging purposes. Garleanu et al. (2009) show that option demand can affect prices because market makers cannot perfectly hedge their positions. Consequently, option prices may reflect the strength and direction of investor demand for option exposure, making them a useful proxy for studying how investors position themselves in underlying stocks and across different anomaly signals.

This dissertation leverages this insight by examining whether option traders systematically position themselves relative to anomaly signals by comparing option-implied synthetic stock prices with the corresponding underlying stock prices. Under demand-based option pricing, a synthetic stock that is more expensive than the underlying stock can be interpreted as reflecting relatively strong demand for obtaining stock exposure through the options market, whereas the opposite pattern suggests weaker demand or bearish positioning. Specifically, discrepancies between synthetic stock positions constructed from options and the corresponding underlying equities provide information about the direction and intensity of investor demand for option exposure on stocks associated with anomaly portfolios. The results indicate that option traders, on average, take positions aligned with the profitable direction implied by many anomaly signals, suggesting that option market participants actively exploit stock return predictability through derivative markets. At the same time, substantial heterogeneity emerges across different categories of anomalies. In particular, traders appear to trade in line with signals related to volatility, momentum, and profitability, while exhibiting weaker or even opposing positioning with respect to other anomaly categories such as value.

This dissertation further analyzes the implications of these findings for the broader debate on the origins of asset pricing anomalies. If option traders systematically take directional positions that align with the profitable side of anomaly strategies, such behavior is more consistent with a mispricing-based interpretation of these anomalies than with a purely risk-based explanation. Building on this intuition, the dissertation develops a novel option market-based measure designed to quantify the extent to which an anomaly signal captures cross-sectional variation in stock mispricing. The measure is motivated by the idea that if option trading activity is primarily driven by profit-oriented trading motives, then stocks with high option trading volume should exhibit greater absolute mispricing. Consequently, anomaly signals that effectively identify mispriced securities should generate stronger returns among such stocks. Applying this framework, the dissertation finds that anomalies related to volatility, momentum, and profitability consistently exhibit high mispricing scores.

Overall, the dissertation makes three contributions to the asset-pricing literature. First, it provides the first systematic evidence on how anomaly returns differ between optionable and non-optionable stocks across a broad set of anomaly categories. The results show that the effects of option listing are not uniform across anomalies and are consistent with options alleviating economically important market frictions, including short-selling constraints, funding constraints, and information frictions. Second, the dissertation develops an options-based approach for inferring how investors position themselves with respect to anomaly signals and shows that option traders often take positions aligned with the profitable side of anomaly strategies. This pattern is particularly pronounced for volatility-, momentum-, and profitability-related anomalies, suggesting that option market participants actively exploit the return predictability associated with these signals. Third, the dissertation develops a novel option market-based measure of the extent to which anomaly signals capture stock mispricing. Applying this measure reveals that volatility, momentum, and profitability anomalies consistently exhibit the strongest mispricing content, mirroring the anomalies for which option traders display the strongest directional positioning. Taken together, these findings demonstrate that information embedded in option markets can be used to identify the mechanisms underlying anomaly returns and thereby shed new light on the sources of cross-sectional return predictability.

1.2 Structure of the Dissertation

This dissertation is structured as follows.

Chapter 2, which is based on the working paper “Anomalies and Optionability” (Böll et al., 2022), examines whether the presence of listed equity options affects the profitability of asset pricing anomalies. The chapter systematically compares anomaly returns between stocks with traded options and stocks without traded options across a broad range of anomaly signals. In particular, the analysis investigates whether the availability of options alleviates market frictions such as short-selling constraints, funding constraints, and information frictions that may contribute to anomaly returns. The results show that the average anomaly remains statistically and economically significant among both optionable and non-optionable stocks. Moreover, differences in average anomaly returns between the two groups can largely be explained by differences in firm characteristics such as size and liquidity. At the same time, the impact of optionability varies considerably across anomaly categories. The evidence indicates that anomalies commonly associated with valuation and return continuation are relatively stronger among non-optionable stocks, whereas anomalies linked to firms’ investment decisions are more pronounced among optionable stocks. These patterns suggest that the effects of option trading on anomaly profitability depend on the underlying economic mechanism and cannot be attributed to a single market friction.

Chapter 3, which builds on the working paper “How Option Traders Take Sides on Return Predictability” (Böll et al., 2025), analyzes whether option traders systematically position themselves relative to anomaly signals. Drawing on insights from demand-based option pricing theory, the chapter compares option-implied synthetic stock prices with the corresponding prices of the underlying stocks and interprets deviations between the two as indicators of directional positioning and option demand. This framework makes it possible to assess whether option market participants trade in the direction implied by profitable anomaly strategies. The analysis reveals that option traders, on average, take positions aligned with the profitable side of many anomaly signals, indicating that derivative markets are actively used to exploit cross-sectional return predictability. In particular, signals related to volatility, momentum, and profitability are associated with especially strong directional positioning in the options market, whereas other anomaly categories exhibit weaker or opposing patterns.

Building on these findings, Chapter 4, which is based on the working paper “Option Trading-Implied Prevalence of Asset Pricing Anomalies” (Böll et al., 2024) develops a framework for quantifying the extent to which anomaly signals capture cross-sectional variation in stock mispricing. The chapter is motivated by the idea that if option trading activity primarily reflects profit-oriented trading motives, then stocks with high option trading volume should exhibit greater absolute mispricing. Based on this intuition, the chapter constructs an option market-based mispricing measure and applies it to a broad set of asset pricing anomalies. The results show that anomalies related to volatility, momentum, and profitability consistently exhibit high mispricing scores, while other anomaly categories such as value or risk exhibit less pronounced mispricing scores.

Finally, Chapter 5 summarizes the main findings of the dissertation and discusses implications for future research.

Chapter 2

Anomalies and Optionability

2.1 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 chapter is the first to provide systematic evidence on how option availability relates to anomaly returns across a broad set of stock anomalies. We investigate if anomaly-related long-short returns differ in magnitude between the group of stocks with traded options and those without traded options. We find significant differences in anomaly returns between these groups. 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

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

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

[3] See for example the discussions in Drechsler and Drechsler, 2021; Hou et al., 2020; Muravyev et al., 2025a.

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 raw returns, the result also generalizes to value-weighted 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. We thus find no evidence of a causal effect of optionability on the strength of the **average** anomaly.

To further investigate potential causal mechanisms, we examine heterogeneity across different types of anomalies. When keeping size and liquidity fixed, we find that "momentum" and "value" anomalies are more pronounced for non-optionable stocks, hinting at roles for short-selling and information frictions in explaining these anomalies. Conversely, we show that "investment" anomalies are stronger on optionable stocks, relative to non-optionables. This finding accords with the literature suggesting that options availability alleviates firms' funding constraints. When aggregating across all anomalies, these opposing effects offset each other.

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

[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.

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.

This chapter 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 et al. (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; Cao et al., 2022; Conrad et al., 2013; Cremers and Weinbaum, 2010; Muravyev et al., 2025b; Xing et al., 2010). 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. An exception is the paper by Abhyankar et al. (2024), which focuses on 12-month momentum, one of the 144 anomalies that we consider.

The chapter 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 Section 2.2. The results of the empirical analysis are presented in Sections 2.3 and 2.4, where Section 2.3 discusses the average anomaly and Section 2.4 zooms into individual anomaly types. Section 2.5 gives a comprehensive overview of the main findings and concludes.

2.2 Data and Empirical Design

2.2.1 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.

OptionMetrics coverage begins in January 1996. Given the 27-day window, our sample starts in February 1996 and ends in December 2018. Figure A.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 A.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 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 chapter.

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.

2.2.2 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 Section 2.2.1, irrespective of optionability. Our sample period generally spans

January 1967 to December 2016,[5] consistent with the original study. Figure A.5 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 2000s, and prior studies suggest that anomaly returns may weaken after publication (see Jacobs and Müller, 2020; McLean and Pontiff, 2016; Schwert, 2003).

Panel A of Figure A.2 compares average monthly anomaly returns over the full 1967-2018 period with those from 1996-2018. 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 Figure A.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.

2.2.3 Empirical Design

Figure A.3 illustrates the distributions of market equity and bid-ask spreads for optionable and non-optionable stocks in a representative month (August 2012). 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 use a bootstrap procedure that constructs samples of optionable and non-optionable stocks with virtually identical distributions of size and liquidity. Unlike a standard

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

bootstrap that samples uniformly, our method assigns selection probabilities inversely proportional to portfolio counts defined by joint sorting 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 distributional matching, they also increase the likelihood of empty portfolios. 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 Appendix A.3.2. Based on 5,000 bootstrap samples, our procedure achieves closely aligned size and liquidity distributions across groups, as illustrated in Figure A.4. Additional bootstraps using uniform sampling probabilities confirm consistency with the original data.

Our bootstrap approach contrasts with traditional 1:1 matching techniques, which often suffer from substantial sample attrition and selection biases. 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 the nonlinear relation between optionability and liquidity (Figure A.3). 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 eligible stocks proportionally, mitigating selection bias and improving the representativeness of inference.

2.3 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 5,000 bootstrap samples.

Table A.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 A.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.

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 Section 2.2.3, 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 A.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 A.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.

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.

To further investigate potential causal mechanisms, Section 2.4 examines heterogeneity across different types of anomalies. Extending the above analogy, one may test (controlling for age) whether watching cartoons is differently associated with specific components of mortality, even if its effect on overall mortality is limited.[6] In a similar spirit, keeping size and liquidity fixed, we find that certain anomalies are more pronounced for optionable stocks, while others are weaker relative to non-optionable stocks. When aggregated, these opposing effects largely offset each other.

2.4 Individual Anomaly Types

2.4.1 Momentum

Table A.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 A.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 Section 2.3.

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, 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 Section 2.3. Rather, momentum exhibits a distinct behavior that runs counter to the aggregate results.

[6] For example, 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.

To understand this discrepancy, we separately examine the long and short legs. Panel B of Table A.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.[7]

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 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.[8]

[7] Garleanu et al. (2009) 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.

[8] 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.

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.

2.4.2 Value

Table A.5 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 Section 2.3, 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 Fama and French, 1992, Table V). Even after adjustment, however, the value premium remains considerably larger for non-optionables.

Compared to the momentum results discussed in Section 2.4.1, 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 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.[9] Informed investors can use options to trade against mipricing, be it under- or overvaluation, and Easley et al. (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.

[9]See Biais and Hillion, 1994; Cao, 1999; Cao et al., 2024; Chakravarty et al., 2004; Easley et al., 1998; Figlewski and Webb, 1993; Hu, 2014, 2018; Jennings and Starks, 1986; Pan and Poteshman, 2006; Roll et al., 2009, 2010; Skinner, 1989, 1990.

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 A.4 and could again hint at a channel related to shorting constraints.

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.

2.4.3 Investment

Table A.6 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, 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 Diamond, 1985; Stiglitz and Weiss, 1981). 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 A.6 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.

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.

2.4.4 Trading Frictions

Table A.7 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.

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.

2.4.5 Profitability and Intangibles

Table A.8 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 A.9 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.

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

2.5 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, this chapter 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.

Chapter 3

How Option Traders Take Sides on Return Predictability

3.1 Introduction

The options market offers informed traders a compelling venue to exploit stock market predictability, attributable to its higher leverage and lower transaction costs Black (1975), while also alleviating short-sale constraints Diamond and Verrecchia (1987). Empirical evidence further indicates that option-based measures possess forecasting power for future stock returns (see, e.g., Cremers and Weinbaum, 2010; Pan and Poteshman, 2006). However, the specific informational signals employed by option traders and the resultant performance of these strategies remain unclear.

In this chapter, we examine how option traders position themselves in relation to stock return predictability arising from stock anomalies. Analyzing option traders' positioning with respect to these anomalies can thus reveal whether traders utilize mispricing information to exploit predictability through the options market. Given the financial leverage offered by options, traders may strategically exploit such opportunities using option contracts. Consequently, directional anomaly portfolios provide a natural framework for identifying which specific signals option traders regard with higher conviction, thereby clarifying the relative predictability of these signals.

We investigate option traders' positioning relative to stock anomalies by quantifying their implied "demand" for exposure to specific anomalies. Guided by the theoretical framework of Garleanu et al. (2009), we infer these implicit demand patterns from observed option prices. According to demand-based option pricing theory, option dealers face limitations—such as transaction costs, discontinuous trading, or jumps in underlying assets—that prevent them from perfectly hedging their positions. These limitations imply that heightened end-user demand for an option can cause its price to deviate from its frictionless theoretical value. Specifically, increased buying pressure for calls and selling pressure for puts tend to drive call prices upward and put prices downward. Consequently, constructing a synthetic stock position (an options position with a delta equal to one) becomes more costly than acquiring the underlying stock directly. Importantly, if traders exhibit substantial trading activity in options on stocks belonging to an anomaly's long portfolio, the synthetic positions replicating these stocks should appreciate in price, rendering them more expensive relative to the stocks themselves. Conversely, the opposite scenario is expected for stocks in an anomaly's short portfolio.

We derive a model-free decomposition of stock excess returns into the return of an option-implied synthetic forward and the excess return of a *conversion trade*. Excess conversion return can thus be interpreted as the discrep- ancy between the actual underlying stock price and the option-implied synthetic stock price. Specifically, it indicates whether the synthetic stock constructed from option prices is relatively underpriced or overpriced compared to the actual stock, thereby revealing potential underlying demand pressures. Following our arguments, if option traders on average trade in a direction that is profitable in relation to an anomaly signal, then the option price can reflect the high demand for those options used for taking exposure the anomaly trading.

Averaged across 243 anomaly signals, we find an average long-short portfolio conversion return of 0.01% (t-statistic of 9.03) per day. This means that in the aggregated anomaly long portfolio the option-implied synthetic stock position is more expensive than the physical stock position, relative to the anomaly short portfolio which reflects that on average option traders trade in a direction that is profitable in relation to a large bulk of anomaly signals.

However, we find pronounced heterogeneity among different groups of anomalies. For example, we find an average long-short portfolio conversion return of 0.01% (t-statistic of 11.07) for anomalies pertaining to the *momentum* category, an average long-short portfolio conversion return of 0.03% (t-statistic of 30.04) for anomalies pertaining to the *volatility* category and an average long-short portfolio conversion return of 0.02% (t-statistic of 19.30) for anomalies pertaining to the *profitability* category. For some other categories, we find negative long-short conversion returns, indicating that option traders take positions that are contrary to the profitable direction relative to these signals. For example, the category *beta* exhibits an average negative long-short portfolio conversion return of -0.01% (t-statistic of -10.41). Similarly, the category *value* also exhibits a negative long-short portfolio conversion return of -0.00% (t-statistic of -2.86).

An interesting question to examine is whether an investor can achieve a profit through conversion trades after accounting for transaction costs. Muravyev and Pearson (2020) show that option trading costs can be substantially reduced when execution timing is optimized. Our results indicate that conversion trades do not present arbitrage opportunities, as the combined stock and option bid-ask spreads exceed the relatively modest effect size of conversion returns.

In addition to conversion returns, we also look at semivariance premia as alternative option price measures. We calculate upside and downside variance premia for anomaly portfolios and find largely consistent results to our analysis using conversion returns. Anomalies pertaining to the categories of *momentum* exhibit an average long-short portfolio upside variance premium of 0.14% (t-statistic of 7.74) and an average long-short portfolio downside variance premium of -0.21% (t-statistic of -13.10). This means that call options in the momentum long portfolio are relatively more expensive than call options in the momentum short portfolio and vice versa for put options, again indicating that option traders take exposure to stocks related to momentum anomalies in a profitable direction. Similarly, the *profitability* category exhibits an average long-short portfolio upside variance premium of 0.49% (t-statistic of 28.09) and an average long-short portfolio downside variance premium of -1.07% (t-statistic of -30.56). For the *volatility* category we find an average long-short portfolio upside variance premium of 0.78% (t-statistic of 20.81) and an average long-short portfolio downside variance premium of -0.95% (t-statistic of -19.85). Consistent to the results we obtain when we use conversion returns as price measure, we find an average long-short portfolio upside variance premium of 0.25% (t-statistic of 7.28) and an average long-short portfolio downside variance premium of 0.62% (t-statistic of 12.23) for anomalies pertaining to the *liquidity* category. For anomalies of the *value* category, we find an average long-short portfolio upside variance premium of -0.24% (t-statistic of -9.71) and an average long-short portfolio downside variance premium of 0.15% (t-statistic of 6.09), indicating that call options are relatively more expensive in the anomaly short portfolio and put options are relatively more expensive in the anomaly long portfolio.

We are also interested in which time periods option traders on average demand options of stocks related to anomaly signals. To this extent, we average long-short portfolio conversion returns across all categories which show consistently positive and significant long-short conversion returns, that are volatility, profitability, issuance and momentum. We relate the aggregate long-short conversion return to various measures of arbitrage frictions such as intermediary capital constraints, the TED spread, shorting fees and bid-ask spreads of stocks and options. Other studies have already established a connection between the gap between synthetic and physical stock prices and frictions: Hiraki and Skiadopoulos (2021) assume the gap as a measure of the impact of frictions on asset prices without empirically demonstrating this relationship. Muravyev et al. (2025b) utilize a related measure, namely the difference between at-the-money call and put implied volatilities, as a gauge for options-implied stock borrowing fees. Our findings suggest that intermediary capital constraints significantly affect the aggregate long-short conversion return, highlighting the important role of financial intermediaries as arbitrageurs.

Related literature Our study makes several contributions to the literature. First, Han et al. (2024) investigates customer option traders' positioning in response to short-term reversal signals. Hollstein and Wese Simen (2024) explores the trading behaviors of option traders across 22 anomalies, classified into three broad categories: options and volatility, liquidity, and accounting and equity trading. While their focus is primarily on option-specific anomalies, with limited attention to stock anomalies, our research takes a different approach. We focus on stock market anomalies, substantially expanding our analysis to include 243 anomalies across 10 categories. Of these, 155 serve as primary predictors for our main analysis.

Second, recent literature has increasingly focused on identifying which anomalies stem from mispricing. For example, Binsbergen et al. (2023) demonstrates that momentum and profitability factors can amplify mispricing in equity markets. Our research extends these findings by showing that option traders construct directional positions specifically designed to correct momentum and profitability mispricing in options markets. In contrast, for value and investment anomalies, option traders' positions merely track the direction of mispricing.

Third, a growing body of literature explores the concept of "smart money" in financial markets. McLean et al. (2020) examine the trading behaviors of nine distinct stock market participants in return predictability and find that firms and short sellers take positions in the profitable direction of anomalies, whereas retail and other institutional investors do not. Da et al. (2024) show that both insider and outsider traders can predict future stock returns, with insider trading having a more enduring impact over time. We contribute to this literature by demonstrating that option traders exhibit "smart" behavior when trading against specific stock anomaly signals, such as momentum and profitability.

Finally, Garleanu et al. (2009) demonstrate that option prices can deviate from their no-arbitrage-implied values when strong demand pressure from option end-users exceeds market makers' hedging capacity. The intermediary literature further establishes that when intermediaries face funding or capital constraints, their ability to arbitrage away mispricings is diminished (Brunnermeier and Pedersen, 2009; He et al., 2017), allowing stock mispricings to persist. We extend this literature by revealing that these constraints can motivate option traders to exploit arbitrage opportunities in the options market.

3.2 Data

We use daily security price and options data from the OptionMetrics Ivy DB database. Our analysis is conducted on a cross-section of common stocks, actively traded at NYSE, AMEX, or Nasdaq. Naturally, our sample is limited to stocks with actively traded options, which leads to the fact that our cross-section consists of rather liquid stocks with large market capitalization. Chapter 2 shows that stock anomalies are on average weaker but still significant on optionable stocks. With respect to the time-series span, our main sample covers the period from January 1996 to June 2021.

We obtain anomaly signals from Chen and Zimmermann (2022) and consider two different set of anomalies. On the one hand, we study all anomalies featured in their data base. On the other hand, we drop all anomalies that they categorize as "placebos" and only consider those they call "predictors". "Placebos" include characteristics that were typically studied by the authors of the original papers for the purpose of benchmarking and did not turn out to have a significant cross-sectional correlation with future returns. To ensure consistency and robustness, we restrict our attention to continuous signals that are not derived from options data (option-based anomaly signals are discussed by Hollstein and Wese Simen, 2024) and that provide sufficient data coverage to compute long-short returns. After applying these filters, we retain 243 signals in the full anomaly set, which we further group into 10 categories using a clustering approach (see Appendix B.3 for details). Table B.4 provides an overview of the 243 anomaly signals used in our analysis.

3.2.1 Conversion Returns

Construction and interpretation. We consider a model-free decomposition of the excess return r^e_S on a non-dividend paying stock with price S into the return r_F on a synthetic forward with price F and the excess return r^e_G on a so-called *conversion trade* with price G. The synthetic forward position consists of a long position in a European call option with price C, maturity T, and strike price X and a short position in a European put option with price P maturity T and strike X. The conversion position G consists of a long position in the stock and a short position in the synthetic forward.

In detail, the return decomposition reads as

$$\begin{aligned} r^e_S &= \frac{S_T - S_0}{S_0} - r_{0,T} \\ &= \frac{F_T - F_0 + (S_T - F_T) - (S_0 - F_0)}{S_0} - r_{0,T} \\ &= \frac{F_T - F_0}{S_0} + \left(\frac{G_T - G_0}{S_0} - r_{0,T} \right) \\ &= r_F + r^e_G, \end{aligned} \tag{3.1}$$

where r_{t_1,t_2} denotes the risk-free interest rate between times t_1 and t_2. Importantly, forward and conversion returns are calculated relative to the stock price S_0 at initiation, rather than the prices of the positions themselves, since the latter can be zero or negative.

For the interpretation of Equation (3.1), it is instrumental to follow Ofek et al. (2004) and define the *synthetic stock price* as

$$S_t^* := C_t - P_t + \frac{X}{1 + r_{t,T}}. \tag{3.2}$$

At maturity, the payout of this option position is S_T, so that $S_T^* = S_T$. In a frictionless environment, $S_t^* = S_t$ must also hold at each point in time t before maturity, a fact commonly referred to as put-call parity. As discussed in Garleanu et al. (2009), if market makers face frictions and cannot perfectly hedge their option positions (for example due to practical reasons, such as a finite hedge frequency, or due to costs, such as capital costs or shorting fees), demand pressure from option-end users can push synthetic stock prices away from their frictionless counterparts. Our analyses in the following sections show that the wedge between synthetic and actual stock prices is cross-sectionally correlated with many anomaly signals, hinting at heightened options end-user demand for exposure to anomaly returns.

For the special case of at-the-money-forward options, i.e., with $X = S_0(1 + r_{0,T})$, substituting Equation (3.2) in Equation (3.1) shows that the returns on the synthetic forward and the conversion have handy interpretations:

$$\begin{aligned} r_F &= \frac{S_T^* - S_0^*}{S_0} - r_{0,T} \\ r_G^e &= \frac{S_0^* - S_0}{S_0} \end{aligned} \tag{3.3}$$

Most importantly, the excess return on the conversion position does not depend on the realization of the stock price at maturity. A conversion built from at-the-money options is a perfectly hedged position and its return is given by the relative price difference between synthetic and physical stock positions at the time of the initiation of the trade.

Empirical measurement. To measure conversion returns, we use option prices from OptionMetrics. More specifically, we use bid and ask quotes of all U.S. equity options written on individual common stocks with standard settlement and expiration dates (i.e., the Friday before the third Saturday in a month or the third Friday in a month after February 1, 2015). Since individual stock options are American, we follow Frazzini and Pedersen (2022) and drop options with a time value below 5% of the options' price to sort out options with a material value of the early exercise option. Moreover, we drop options on stocks that pay dividends between the conversion formation date and the expiry date of the options.

Then, for each day and stock in our sample, we select a pair of call and put options expiring at the upcoming standard maturity date. We follow Jacobs et al. (2026) and switch to the standard maturity after the next maturity (i.e. to the next month), if time to maturity is shorter than 15 days. This procedure avoids using prices of options with very short maturities, which can be driven by short-term speculation and traders rolling over maturing positions to options with longer maturities or weeklys. As a consequence, all options in our sample have times-to-maturity between 15 and 49 days.

We select a pair of options whose strike prices are closest to the forward price of the stock. We drop the stock-day if the moneyness deviates by more than 10% from at-the-money forward. We also drop stock-days where one of the two options has zero open interest or zero trading volume. Furthermore, we follow Goyal and Saretto (2009) and only keep option observations with a positive implied volatility, a positive bid price, and a bid-ask spread larger than the minimum tick size. Finally, we drop options where the bid-ask midpoint price violates standard arbitrage bounds.

Conversion prices are calculated from mid prices between bid and ask of all asset involved. We are aware of the fact that actual investors cannot trade at the mid. The goal of our analysis is not to demonstrate that there are arbitrage opportunities in the options market. Indeed, we show in Section 3.3.4 that transaction costs exceed conversion returns by a large margin. Still, conversion returns tell us if option mid prices move away from their frictionless counterparts, indicating heightened demand for that option.

To calculate gains on the conversion trade, we subtract the conversion price at initiation from the strike, which is equal to the payoff of the conversion at maturity. The conversion return is then given by the ratio of this gain and the stock price at initiation. Note that this return is not a daily return (in the sense that the holding period is one day), but the conversion is assumed to be held until maturity of the option. Since the portfolio payoff at option maturity is known at the formation date, it can always be compared to a riskless investment in a money market account. To calculate excess returns, we subtract the short rate reported by OptionMetrics for the respective time-to-maturity.

We form decile portfolios, according to the anomaly signals, on each day in our sample, using characteristics from the end of the previous month. Portfolio breakpoints can vary from day to day, due to varying availability of liquid option contracts. We report average conversion return differences across decile portfolios. Since the positions have to be held between 15 and 48 days, our average returns can be interpreted as monthly returns, again, with the understanding that conversion returns are price differences and, therefore, known at the initiation of the trade.

Summary statistics. Panel A of Table B.1 shows summary statistics of of our sample of (excess) conversion returns, pooled across assets and time. The sample consists of around 9 million observations, corresponding to a cross-section of around 1370 stocks per day. The average excess conversion return is -7 basis points. This could hint at two channels. First, the interest rate used to calculate excess returns could be higher on average than the interest rate implied by the options used in our sample. Second, high average demand or low market maker supply for put options, relative to call options, could, on average, pull excess conversions to the negative domain. Since our later analysis will focus on spreads in conversions across different anomaly portfolios, the level of excess conversion returns is of secondary interest to our analysis.

More interestingly, there is pronounced variation in conversion returns with a pooled standard deviation of around 0.4 percent. Our analysis in Section 3.3 shows that this variation is cross-sectionally correlated with many anomaly signals, hinting at pronounced option demand for specific underlyings.

3.2.2 Semivariance Premia

Construction and interpretation. A positive conversion return difference between anomaly portfolios can only hint at a heightened demand for calls written on stocks in the long anomaly portfolio *or* a heightened demand for puts on stocks in the short anomaly portfolio. We use semivariance premia, as in Kilic and Shaliastovich (2019) and Held et al. (2020), as measures for the expensiveness of call and put options, to allow a distinction between the two channels. Intuitively, an upper (lower) semivariance premium is given by the difference between the option-implied variances from at-the-money and out-of-the-money call (put) options and the variance in the positive (negative) return domain under the physical measure. High semivariance premia indicate that calls/puts are expensive vis-a-vis the characteristics of the underlying (especially its variance), hinting at a heightened demand for the option.

The upper (lower) semivariance of a random variable Z is defined as the expected squared difference between Z and its mean, conditional on that difference being positive (negative). For logarithmic returns on stock i, Kilic and Shaliastovich (2019) and Held et al. (2020) show how to decompose the expression for the model-free option-implied variance (see Bakshi et al., 2003; Carr and Madan, 2001) into the lower semivariance $SV_t^{\mathbb{Q}-}$ and the upper semivariance $SV_t^{\mathbb{Q}+}$ under the risk-neutral measure $\mathbb{Q}$:

$$SV_t^{\mathbb{Q}-} = \int_0^{S_t(1+r_{t,T})} \frac{2(1+\log(S_t(1+r_{t,T})/X))}{X^2} P_t(T-t,X)dX \tag{3.4}$$

$$SV_t^{\mathbb{Q}+} = \int_{S_t(1+r_{t,T})}^{\infty} \frac{2(1-\log(X/S_t(1+r_{t,T})))}{X^2} C_t(T-t,X)dX. \tag{3.5}$$

Here, we augmented our notation of C and P from Section 3.2.1 to make explicit that the options have strike prices X and time-to-maturities $T-t$. For the ease of notation, we omit the stock index i from all operators, with the implicit understanding that all computations will be performed for each stock individually.

Empirical measurement. To empirically estimate the option-implied semivariances, we follow the methodologies outlined in Carr and Wu (2009) and Chang et al. (2012). Specifically, we back out the prices of European call and put options from the volatility surface file provided by OptionMetrics. The file provides implied volatilities for standardized ranges of maturities and option deltas, calculated by spline-interpolating the implied volatilities of available options. The latter are calculated using a binomial tree method.

Consistent with the conversions, estimated as explained in Section 3.2.1, we select a time-to-maturity of 30 days. Since the surface file often reports negative implied volatilities, we drop stock-days with less than four distinct positive call or put implied volatilities. We approximate the integrals in Equations (C.1) and (C.2) by calculating out-of-the-money call and put prices corresponding to 1000 moneyness levels each. For that purpose, we apply a cubic smoothing spline across moneyness values ranging from 0.3% to 300%. Here, moneyness is defined as the ratio of the strike price to the ex-dividend stock price, the latter being calculated as the difference between the time t stock price and all dividend payments between t and T.

Following Jiang and Tian (2005), to address potential interpolation and extrapolation issues, we set the implied volatilities for moneyness levels beyond the observed range in the OptionMetrics data to the corresponding implied volatilities at the boundary moneyness values. We then calculate option prices, by substituting the interpolated implied volatilities, together with the other relevant option characteristics into the Black and Scholes (1973) formula. Finally, we implement the trapezoidal rule to numerically compute the risk-neutral semivariances in Equation C.1 and Equation C.2.

To estimate semivariances under the physical measure $\mathbb{P}$, we again follow Kilic and Shaliastovich (2019) and use the fitted value from a time series model. In particular, we generalize the approach of Bekaert and Hoerova (2014) to semivariances by running the following predictive time series regressions on daily stock return data from the OptionMetrics security price file:

$$\begin{aligned} RV^{-}_{\tau+1,\tau+22} = a^{-} &+ b^{-}_{1} SV^{\mathbb{Q}-}_{\tau} + b^{-}_{2} SV^{\mathbb{Q}+}_{\tau} + b^{-}_{3} RV^{-}_{\tau-21,\tau} + b^{-}_{4} RV^{+}_{\tau-21,\tau} \\ &+ b^{-}_{5} RV^{-}_{\tau-4,\tau} + b^{-}_{6} RV^{+}_{\tau-4,\tau} + b^{-}_{7} RV^{-}_{\tau,\tau} + b^{-}_{8} RV^{+}_{\tau,\tau} + \varepsilon^{+}_{\tau+1,\tau+22} \end{aligned} \tag{3.6}$$

$$\begin{aligned} RV^{+}_{\tau+1,\tau+22} = a^{+} &+ b^{+}_{1} SV^{\mathbb{Q}-}_{\tau} + b^{+}_{2} SV^{\mathbb{Q}+}_{\tau} + b^{+}_{3} RV^{-}_{\tau-21,\tau} + b^{+}_{4} RV^{+}_{\tau-21,\tau} \\ &+ b^{+}_{5} RV^{-}_{\tau-4,\tau} + b^{+}_{6} RV^{+}_{\tau-4,\tau} + b^{+}_{7} RV^{-}_{\tau,\tau} + b^{+}_{8} RV^{+}_{\tau,\tau} + \varepsilon^{-}_{\tau+1,\tau+22} \end{aligned} \tag{3.7}$$

where $RV^{*}_{\tau_1,\tau_2}$ with $\tau_1 < \tau_2$ and $* \in \{-,+\}$ is defined by

$$RV^{+}_{\tau_1,\tau_2} = \sum_{\tau=\tau_1}^{\tau_2} r^2_{\tau} 1_{r_\tau>0} \quad \text{and} \quad RV^{-}_{\tau_1,\tau_2} = \sum_{\tau=\tau_1}^{\tau_2} r^2_{\tau} 1_{r_\tau<0} \tag{3.8}$$

We calculate expectations for the next 22 trading days, which is equivalent to the 30 days-to-maturity convention of OptionMetrics. We run regressions C.3 and C.4 separately for each stock using the full sample period. We use the estimated coefficients to estimate the semi-variances for each stock on each day t and $* \in \{-,+\}$ as

$$\begin{aligned} SV_t^{\mathbb{P}*} = a^+ + b_1^* SV_t^{\mathbb{Q}-} + b_2^* SV_t^{\mathbb{Q}+} + b_3^* RV_{t-21,t}^- + b_4^* RV_{t-21,t}^+ \\ + b_5^* RV_{t-4,t}^- + b_6^* RV_{t-4,t}^+ + b_7^* RV_t^- + b_8^+ RV_{t,t}^+. \end{aligned} \tag{3.9}$$

Finally, we compute daily stock-specific semi-variance risk premia as

$$SVP_t^- = SV_t^{\mathbb{Q}-} - SV_t^{\mathbb{P}-} \quad \text{and} \quad SVP_t^+ = SV_t^{\mathbb{Q}+} - SV_t^{\mathbb{P}+} \tag{3.10}$$

By construction, the semi-variance risk premia add up to the total variance risk premia. This is true since the physical semivariance estimates employ the same predictive variables in both of the equations (C.3) and (C.4). In our later analysis, $SVP_{i,t}^-$ is interpreted as a measure for the expensiveness of put options and $SVP_{i,t}^+$ is our measure for the expensiveness of call options for stock i on day t.

When calculating the implied volatility of an option with a particular maturity and strike, OptionMetrics interpolated between all existing neighboring maturities and strikes and employs a kernel approach with weights corresponding to the distances between the maturities and strikes of the available option with the targeted characteristics. Importantly, for the call (put) surface, the algorithm can also use put (call) implied volatilities, which are, however, assigned a negligible weight, if a sufficient number of calls (puts) are available. This circumstance could hamper our analysis, as it works against us. On average, however, out-of-the-money options are typically more liquid than in-the-money options, so that we expect the implied volatility surface file for calls (puts) to be largely dominated by information from call (put) options.

Summary statistics. Panel B of Table B.1 presents summary statistics for the lower and upper semivariance premia. On average, the upper semivariance premium is negative at -0.14, while the lower semivariance premium is positive at 0.40. This asymmetry aligns with existing empirical evidence, such as Kilic and Shaliastovich (2019) and Held et al. (2020) for index options. The average total variance premium is positive at 0.22 percent, in line with earlier findings from Hollstein and Simen (2020).

3.3 Anomaly Portfolios in Stock and Options Markets

We want to study whether the demand pressures from option market participants align with anomaly signals in the cross-section. To profit from an anomaly, option traders build option positions with positive exposures to stocks in the long portfolio, that is, buy calls or write puts. Garleanu et al. (2009) show that option dealers cannot hedge their positions perfectly for various reasons, such as transaction costs, the inability to trade continuously, or jumps in the underlying. This inability results in the fact that an increase in end-user demand for an option can drive its price away from its frictionless counterpart. According to demand-based option pricing theory, increased buying pressure for calls and selling pressure for puts lead to higher call prices and lower put prices. In this case, acquiring a synthetic stock position (an options position with a delta of one) is more expensive than buying the stock position itself.

Importantly, if traders heavily trade in options of stocks in an anomaly long portfolio, the option positions replicating these stocks should increase in price, meaning that the synthetic stock positions are more expensive than the stocks themselves. The exact opposite should hold for stocks in an anomaly short portfolio. Therefore, a positive long-short difference in conversion returns corresponding to an anomaly signal suggests that the marginal options investor trades against an anomaly, in the sense that she enters a long position in stocks with high returns and/or a short position in stocks with low returns, according to the anomaly signal.

While the conversion excess returns tell us only if the combination of a long call and a short put position is relatively expensive for a given stock, semivariance premia can inform us whether the observed patterns in conversion returns are driven by call or put demand.

3.3.1 The Average Anomaly

To get an initial impression and before we discuss individual anomalies, we consider the average anomaly. To do this, we compute equally weighted averages of the portfolio returns for all anomaly-long portfolios and all anomaly-short portfolios, and examine the differences. Table B.2 shows the results in Panel A when we average over all 243 signals in our sample.

We find a difference in the conversion returns between the average anomaly-long and the anomaly-short portfolio of around 0.007% per day. Although this value is very small, it is very precisely estimated, with a t-statistic of 9.03. This high precision is due to the fact that conversion returns are price differences, not highly volatile returns that are subject to uncertainty over the holding period. Additionally, we average over 243 time series and over 6,600 time points.

A look at the associated semi-variance premia shows that this difference is driven by both calls and puts. We observe higher upper semi-variance premiums in the aggregated anomaly portfolio 10 compared to portfolio 1, meaning that call options on stocks in portfolio 10 have a higher demand on average than those on stocks in portfolio 1. For puts, the exact opposite holds true. The lower semi-variance risk premia of stocks in portfolio 1 are significantly higher than those of stocks in portfolio 10. This means that the marginal options investor is more likely to demand put options that provide a negative exposure to stock movements of underlyings that, according to the average anomaly signal, are overpriced, relative to those that are underpriced. In summary, this result indicates that options investors, on average, take a profitable side in stock anomalies.

Panel B shows the same statistics, but we now average across those 155 anomalies that are labeled as "predictors" by Chen and Zimmermann (2022). If options investors only trade against profitable anomalies, we should exclude "placebos" from the analysis. The average return difference on stocks in predictor-sorted decile portfolios is rather similar to the the average return difference associated to all signals. This points to the fact that the optionable sample between 1996 and 2021 is different from the original samples the predictors and placebos have been tested in. The conversion spread is again positive and larger than in Panel A. The semivariance premia are consistent with this finding. The spread in upper semivariance premia is larger and the spread in lower semivariance premia is lower on the set of predictors than on the full set of anomaly signals.

Some of the predictors on the full sample could turn out uninformative on the set of optionable stocks. As discussed in Chapter 2, optionable stocks are rather liquid and have large market capitalization on average. It is well-known that some anomalies do not yield significant returns on such stocks. For Panel C, we only average across anomaly signals with significantly positive average returns on the set of optionable stocks between 1996 and 2021. Several anomaly signals happen to yield even significantly negative returns on our sample, although we sign all anomaly signals according to the sign suggested in the original papers.

The spread in average stock returns is, by construction, higher for significant signals than on the other two sets of signals. However, we also see a fairly large increase in the conversion spread. The difference between conversion returns in the high and low anomaly portfolios amounts to around 0.012%. In other words, when looking exclusively at anomalies that are strong on the sample of stocks used in our analysis, we find that anomalies are larger on the stock market than on the options market and the difference amounts to around one basis point per day. The massive semivariance premia, especially on the downside, indicate that investors use calls and puts, but primarily the latter, to trade against anomalies in the options market.

3.3.2 Individual Anomalies

Table B.5 shows stock, forward and conversion return differences between the long and the short decile portfolio corresponding to all 243 individual anomaly signals in our sample. Likewise, Table B.6 shows long-short differences in upper and lower semivariance premia. We find strong variation in conversion excess returns and semivariance premia across different kinds of anomalies. We discuss a few prominent examples here.

The momentum anomaly *Mom12m* exhibits a long-short conversion return difference of 0.03% (t-statistic of 11.67). This indicates that on average there is demand for trading against stocks in the momentum short portfolio using options, e.g. by buying puts or selling calls. An alternative explanation of the positive long-short conversion return could be that option traders buy calls or sell puts in the momentum long portfolio. In any case, the positive long-short portfolio conversion return for the momentum anomaly indicates that on average option traders trade in a direction that is profitable to them in relation to this anomaly signal.

Again starting with the momentum anomaly *Mom12m*, we find a long-short portfolio downside variance premium of -0.67% (t-statistic of -19.11). This means that put options in the momentum short portfolio are relatively more expensive than in the anomaly long portfolio. Looking at the upside variance premium, we find a long-short portfolio upside variance premium of 0.52% (t-statistic of 10.98). This suggests that call options in the momentum long portfolio are more expensive compared to those in the momentum short portfolio.

Another anomaly where we find positive and significant long-short conversion returns is the profitability anomaly *CBOperProf*. The anomaly's long-short conversion return is 0.04% (t-statistic of 18.50). This again indicates that on average option traders use options to get exposure to stocks related to this anomaly in a direction that is profitable to them.

The long-short portfolio downside variance premium is -1.45% (t-statistic of -24.41). Similar to before, this implies that puts in the profitability anomaly's short portfolio are relatively more expensive than in the anomaly's long portfolio. For the upside variance premium we find a positive long-short portfolio upside variance premium of 0.57% (t-statistic of 26.66), meaning that calls are relatively expensive in the long portfolio of this anomaly. Following demand-based option pricing theory, this indicates that option traders demand call and put options in directions that are profitable to them relative to this anomaly signal.

However, there is heterogeneity among anomalies. For example, the book-to-market ratio *BM*, a classic value anomaly, exhibits a negative long-short conversion return of -0.01% (t-statistic of -2.17). This finding suggests that for this anomaly, option traders take exposure to stocks related to this anomaly in a direction that is not profitable to them.

3.3.3 Anomaly Categories

To better understand the heterogeneity among types of anomalies, we classify the anomalies into ten economic categories based on pairwise return correlations. The clustering methodology is detailed in Appendix B.3. Figure B.1 presents the average long-short conversion returns across these categories, with the economic categories shown on the x-axis and corresponding returns on the y-axis. Red error bars represent 95% confidence intervals for the mean, with standard errors adjusted following Newey and West (1987).

The *volatility* category exhibits the highest average long-short conversion return of 0.03% (t-statistic = 30.04), primarily driven by the anomaly *IdioVolAHT*, which delivers an individual effect with a return of 0.09% (t-statistic = 32.47). The category with the second-highest average long-short excess conversion return is *profitability*, largely due to the anomaly *CBOperProf*, a cash-based operating profitability measure introduced by Ball et al. (2016). Within the *issuance* category, the anomaly *ShareIss1Y* generates the highest individual long-short excess conversion return of 0.03% (t-statistic = 16.36). Other categories in which option market activity aligns with anomaly-based return predictability include *momentum* and *accurals*, among others. Conversely, option trader positioning appears to be against the profitable anomaly direction in categories such as *value* and *beta* and *liquidity*. The *liquidity* category exhibits the most negative long-short conversion return at -0.01% (t-statistic = -11.74).

We also plot long-short semivariance premia that are averaged across the 10 clusters. The results are shown in Figure B.3. The bar plot in green shows the long-short upside variance premium on the y-axis. The bar plot in orange shows the long-short downside variance premium on the y-axis. The x-axis depicts the 10 categories. The error bars in red indicate a 95% confidence interval for the mean. Importantly, we do not sort long-short semivariance premia according to their level, but instead keep the order from Figure B.1 to be able to easily compare the results for the different option price measures. We find remarkably consistent results compared to those when using the conversion excess returns as a price measure. Categories for which we find positive and economically significant long-short conversion returns in general also show positive and significant long-short upside variance premia and negative and significant long-short downside variance premia. Such categories are, for example, *volatility, profitability, issuance and momentum*. Our results indicate that for these categories option traders demand options in a direction that is profitable to them.

Categories exhibiting negative long-short conversion returns generally display negligible or negative long-short upside variance premia coupled with positive long-short downside variance premia, demonstrating internal consistency in our findings. This pattern is particularly evident in the *intangibles* and *value* categories, where option traders pursue positions in directions that ultimately prove unprofitable for them. For *liquidity*, we observe mixed results: both upper and lower semivariance measures are positive. This indicates that option traders successfully position themselves for profitable exposure in long-leg stocks but fail to do so with short-leg stocks. Notably, the magnitude of “losses” incurred from incorrect selling put options is approximately twice the “gains” realized from correct buying call.

3.3.4 Transaction Costs

We are also interested if an investor could generate a profit engaging in conversion trades. In order to execute a conversion trade, the investor must buy the stock and short the option-implied synthetic forward of that stock, which entails writing a call option and buying a put option on that stock. This implies that the long-short conversion return of a specific strategy must exceed the three bid-ask spreads, related to the stock, put and call.

Specifically, we calculate the average call, put and stock spreads in an anomaly long and short portfolio and add the averages to get an estimate of the trading costs. We collect call and put option quoted spreads from OptionMetrics. Muravyev and Pearson (2020) show that the effective spreads that option traders pay are significantly smaller than the quoted spreads, especially when they time their trades. We calculate multipliers based on Table 5 of the paper (S&P 500 stocks) and on Table IA.5 of the internet appendix (non-S&P 500 stocks). Specifically, we consider their dollar-based half-spreads of ATM options and calculate multipliers as $\frac{\text{Effective half-spread}}{\text{Quoted half-spread}}$, $\frac{\text{Adjusted half-spread}}{\text{Quoted half-spread}}$, and $\frac{\text{Algo half-spread}}{\text{Quoted half-spread}}$. We do this for S&P 500 stocks as well as non-S&P 500 stocks and average the results. We then take our quoted half-spreads from OptionMetrics and multiply them by the multipliers to derive our option trading costs estimate. For the stock trading costs, we rely on the CRSP quoted half-spread as an approximation for the effective spread. Figure B.2 shows the results.

The blue bars indicate the long-short conversion return of the respective anomaly category. The red bars indicate the corresponding trading costs centered around the mean conversion long-short return. Considering the small effect size of the long-short conversion returns, it is not surprising that we do not find a single category that would generate a positive profit after adjusting for trading costs. For all categories, the red confidence intervals includes zero, indicating that the conversion long-short return would be below zero after trading costs.

3.4 The Impact of Frictions

3.4.1 Empirical Design and Data

We investigate the timing of option traders' activities in taking positions related to anomaly signals. To this extent, we average long-short portfolio conversion returns across all anomaly signals which we use in our study and relate the aggregate long-short conversion return to various measures of frictions such as intermediary capital constraints, funding friction, short-selling frictions, and bid-ask spreads of stocks and options.

Intermediary Capital Constraints Prior research highlights the pivotal role of financial intermediaries as marginal investors across a range of intermediated asset classes, including the options market (Adrian et al., 2014; Haddad and Muir, 2021; He et al., 2017). To account for the influence of intermediary capital constraints, we employ the intermediary capital ratio (denoted by ICR) proposed by He et al. (2017) as a proxy.

Funding Liquidity Constraints To proxy funding conditions within the financial intermediary sector, we utilize the TED spread (denoted by TED), which is defined as the difference between the 3-month LIBOR rate and the 3-month Treasury bill rate. The TED spread serves as a measure of credit risk and funding stress in the banking system. Data on the TED spread is sourced from the Federal Reserve Bank of St. Louis.

Short-Selling Constraints We use Markit's INDICATIVEFEE as a proxy for short-selling constraints, which reflects the expected borrowing cost faced by hedge funds on a given day. To construct the shorting fee measure, we first compute the monthly average shorting fee for each stock with non-missing conversion return data. Subsequently, we calculate cross-sectional averages across stocks each month to obtain a time series of shorting fees, denoted by SF. As the dataset provides coverage of a sufficiently broad cross-section of stocks only from July 2006 onward, our analysis spans the period from August 2006 to June 2021.

Liquidity Constraints on the Stock Market Liquidity constraints in both the stock and options markets can influence the ability to use options for exposure to stocks associated with anomaly signals, either facilitating or restricting such activity. To quantify these constraints, we employ bid-ask spreads as a measure of market liquidity. For stocks, we utilize the bid-ask spread estimator proposed by Corwin and Schultz (2012). To construct the time series of stock bid-ask spreads, denoted by $Bidask^{stock}$, we first compute the monthly average spread for each stock with non-missing conversion return data and subsequently take cross-sectional averages across stocks in each month.

Liquidity Constraints on the Options Market For options, we use the leverage-adjusted option liquidity measure developed by Götz et al. (2025). For that purpose, we compute the quoted bid-ask spread of call options relative to the mid-price of the best bid and ask and then divide by the option's delta times the price of the underlying stock. Götz et al. (2025) show that this measure has better properties than the relative bid-ask spread itself. To construct the time series of option bid-ask spreads, denoted by $Bidask^{call}$, we proceed similarly to our procedure when constructing the stock liquidity time series.

We estimate the following time-series regression, based on monthly data:

$$\begin{aligned} r^{ls}_{C,t} = \alpha_a &+ \beta_{a,icr}\, ICR_{t-1} + \beta_{a,ted}\, TED_{t-1} + \beta_{a,bas}\, Bidask^{stock}_{t-1} \\ &+ \beta_{a,bao}\, Bidask^{call}_{t-1} + \beta_{a,sf}\, SF_{t-1} + \beta_{a,lag}\, r^{ls}_{C,t-1} + \epsilon_{a,t}, \end{aligned} \tag{3.11}$$

where $r^{ls}_{C,t}$ is the conversion long-short return of the average anomaly in month t. Since all friction measures are realized at the end of the month prior to the initiation of the conversion positions Equation (3.11) is a predictive regression.

3.4.2 Empirical Findings

Table B.3 presents the regression results. Columns (1) to (5) report estimates from univariate regressions, while column (6) provides results from a multivariate regression incorporating all friction measures. In the univariate specifications, the intermediary capital ratio is negatively and significantly related to conversion returns, with a coefficient of -0.23 and a t-statistic of -3.87. This finding suggests that conversion returns tend to be higher in periods of elevated intermediary capital constraints (corresponding to a low ICR).

However, in the multivariate regression, not only the intermediary capital ratio remains statistically significant, with a coefficient of -0.12 and a t-statistic of -3.96, but also the TED-spread becomes statistically significant with a coefficient of 0.26 and a t-statistic of 3.72. Stock illiquidity turns significant at the 10% level with a coefficient of -0.05 and t-statistic of -1.89. These results highlight the role of financial intermediaries as key arbitrageurs in the options market, particularly when arbitrage capital is abundant. Interestingly, short-selling constraints do not turn out to be significantly related to conversion spreads in the time series.

3.4.3 Discussion

How can we interpret the finding that conversion spreads are large when intermediary capital ratios are low, indicating severe capital constraints on part of large financial intermediaries? He et al. (2017) define this measure as the ratio of equity capital and total capital of primary dealers in the US. These banks act in several roles in the stock and derivatives market, so that we can think of (at least) two different channels, when interpreting our results:

First, drawing on the work of He and Krishnamurthy (2013) and He et al. (2017), we can hypothesize that capital constraints affect financial intermediaries that trade risky assets on their own books. Under normal circumstances, these intermediaries trade against anomalies in the stock market, helping to mitigate them. However, a reduction in their risk-bearing capacity makes such trades costly. As a result, during these periods, anomalies become more pronounced, creating opportunities for other sophisticated traders, such as hedge funds, to exploit them. These traders often turn to the options market to do so, taking advantage of low funding and short-selling costs. If options market makers are unable to perfectly hedge their positions (Garleanu et al., 2009), the increased demand for specific options drives conversion returns away from zero. Importantly, this explanation highlights the central role of intermediary capital constraints in the economic explanation of asset pricing anomalies.

A second possible explanation is that investors trade against anomalies in the options market, but their demand for options is not directly linked to the severity of capital constraints. Instead, we might suggest that capital constraints primarily affect options market makers. As per Garleanu et al. (2009), market makers are risk-sensitive and cannot perfectly hedge their positions in the stock market. When their risk-bearing capacity is low, they reduce the supply of options, which leads to higher conversion returns. Crucially, this second explanation emphasizes that conversion returns are driven by changes in market maker supply, rather than by option end-user demand, as in the first explanation.

3.5 Conclusion

In this chapter, we look at how options traders take sides on the predictability of the underlying stocks, using a wide array of cross-sectional return predictors. We do this by building on the argument of Garleanu et al. (2009). Demand-based option pricing theory suggests that option prices may deviate from their frictionless benchmarks due to imperfect hedging by option dealers responding to collective trading demand pressure from option end-users. Consequently, option prices reflect aggregate demand pressure and thus provide valuable insights into the trading behavior of option market participants, enabling us to examine how these traders align themselves with well-know stock predictors.

We employ two measures derived from option prices — excess conversion returns and semi-variance premia — to capture this demand pressure under the framework of demand-based option pricing theory. The first measure, the excess conversion return, is constructed using a model-free decomposition of stock excess returns into a synthetic forward return and an excess conversion return. Excess conversion returns can thus be interpreted as the discrepancy between the actual underlying stock price and the option-implied synthetic stock price. Specifically, it indicates whether the synthetic stock constructed from option prices is relatively underpriced or overpriced compared to the actual stock, thereby revealing demand pressure in options. According to demand-based option pricing theory, if option traders consistently take positions aligned with the profitable direction suggested by a given anomaly signal, we expect to observe a positive and statistically significant conversion return for the corresponding long-short anomaly portfolio.

When averaging across all anomaly signals in our sample, we find an average long-short conversion of around one basis point per month. Although this number seems tiny, it is estimated with great precision and highly significant. Importantly, conversion returns are known at trade initiation: They are given by the relative price difference between the stock and the replicating option portfolio. Consequently, we find that option traders are, on average, on the profitable side of return predictability, according to cross-sectional stock anomaly signals.

However, there is significant heterogeneity across anomaly categories. Specifically, anomalies in the *momentum*, *volatility*, *profitability*, and *issuance* groups yield large, positive average long-short portfolio conversion returns. This suggests strong demand for options that enable traders to establish directional positions to correct mispricings associated with these anomalies.

In contrast, anomalies related to *beta*, *value*, and *liquidity* produce negative conversion returns, indicating that option traders may not be actively exploiting these mispricing signals but are instead merely tracking contemporaneous stock mispricings during the holding period. However, many *value* and *liquidity* anomalies signals are not positively related to future returns. One could assume that option traders are aware of the fact that for example the value anomaly does not work well on the sample of optionable stocks between 1996 and 2021 (see, e.g., Arnott et al., 2021) and rather sought positive exposure to the well-performing growth stocks in the optionable sample, such as Amazon, Apple, Facebook, Google, Microsoft, or Netflix.

The semivariance premium complements the excess conversion return measure by indicating whether demand pressure predominantly originates from call or put trading. Our analysis of semivariance premia produces findings consistent with those based on excess conversion returns. Specifically, anomaly categories characterized by positive and significant long-short conversion returns—*profitability*, *issuance*, *momentum*, and *volatility*—tend to exhibit positive long-short upside variance premia and negative long-short downside variance premia. This pattern suggests that option traders actively utilize both call *and* put options to position themselves profitably relative to the anomaly signals. Conversely, anomaly categories associated with negative long-short conversion returns, namely *value* and *beta*, generally exhibit the opposite pattern.

Lastly, we investigate the temporal relation between long-short portfolio conversion returns and measures of several frictions. We find strong evidence that conversion spreads are particularly pronounced when the intermediary capital ratio is low, indicating low risk bearing capacity on part of large banks. One natural interpretation of this pattern is that stock anomalies are particularly pronounced at times when intermediary capital constraints are binding. Under normal circumstances, large intermediaries trade against anomalies in the stock market, helping to mitigate them. However, a reduction in their risk-bearing capacity makes such trades costly. As a result, during these periods, anomalies become more pronounced, creating opportunities for other sophisticated traders, such as hedge funds, to exploit them. These traders often turn to the options market to do so, taking advantage of low funding and short-selling costs. If options market makers are unable to perfectly hedge their positions (Garleanu et al., 2009), the increased demand for specific options drives conversion returns away from zero.

The channel discussed above suggests that intermediary capital constraints not only play an important role in explaining conversion returns but also in explaining the anomaly returns themselves. Since stock returns are much more volatile than conversion returns, a direct investigation into whether anomaly returns are more pronounced during times of binding capital constraints is difficult. Our results thus provide an important confirmation of the channel proposed by He et al. (2017) , explaining anomalous stock return differences in the cross-section via capital constraints of intermediaries.

Chapter 4

Option Trading-Implied Prevalence of Asset Pricing Anomalies

4.1 Introduction

In recent years, the empirical asset pricing literature has discerned a large number of patterns in the cross-section of expected stock returns (see, e.g., Chen and Zimmermann, 2022; Jensen et al., 2023). Many of these patterns yield economically substantial and statistically significant alphas relative to conventional asset pricing models, such as the three-factor model of Fama and French (1993) and its various extensions. In the finance literature, these patterns are commonly referred to as *anomalies*. However, the economic mechanisms underlying these patterns remain contested. We show that option trading activity provides a market-based diagnostic that helps distinguish whether anomaly returns reflect risk premia or the correction of prior mispricing.

We document that anomaly returns are disproportionately concentrated among stocks with high option trading activity. To quantify this phenomenon, we propose the *Option Trading-Implied Prevalence* (OTP), defined as the difference between the anomaly return among stocks in the top quintile of option trading activity, measured by the option-to-stock trading ratio O/S following Roll et al. (2010), and the unconditional anomaly return. The intuition is that option trading can reflect either hedging of risk exposures or speculative trading on mispricing; therefore, the extent to which anomaly returns concentrate among option-active stocks is informative about whether a signal reflects risk premia or mispricing.

Our empirical analysis yields three main findings. First, OTP is positive on average and varies substantially across anomaly types: volatility, momentum, profitability, and issuance exhibit consistently high OTP, whereas accruals, risk, intangibles, and value show weak or negative OTP. Second, across anomalies, OTP aligns closely with established mispricing classifications and with elevated earnings-announcement returns. Third, using structurally identified option demand shocks, we show that high-OTP signals predict directional end-user positioning, with increased call demand and reduced put demand, consistent with informed trading on mispricing.

We begin by examining the average anomaly portfolio, defined as an equal-weighted portfolio of all anomaly-related long-short strategies in our sample. The unconditional return of this portfolio is 0.29% per month, but rises to 0.40% when restricting attention to stocks with high option trading activity. The resulting OTP of 0.11% per month indicates that anomaly returns are disproportionately concentrated among option-active stocks.

To better understand the economic interpretation of OTP, we study its variation across anomalies and compare it with existing anomaly classifications proposed in the literature. These classifications provide external benchmarks for distinguishing between anomalies attributed to mispricing and those attributed to risk compensation. As a first plausibility check, we find that anomalies with higher OTP values tend to exhibit larger unconditional alphas relative to standard asset pricing models, consistent with a mispricing-based interpretation. We then consider the classification of Chen et al. (2023), which groups anomalies according to the economic interpretations proposed in the original studies. Anomalies classified as mispricing-based exhibit a pronounced amplification of returns among stocks with high option trading activity, whereas anomalies classified as risk-based show essentially no amplification across option volume quintiles.

We further compare OTP to two additional mispricing measures proposed in the literature. The first is the measure introduced by Bali et al. (2023), which identifies mispricing as deviations from the fair rate of return implied by an IPCA model. The second is the measure proposed by Frey (2023), which classifies anomaly signals according to their ability to predict analysts' earnings forecast revisions. Across anomalies, OTP is strongly positively correlated with Frey's measure, suggesting that anomalies with high OTP values are associated with predictable errors in investor expectations about firms' future earnings and are therefore more likely to reflect mispricing.

Additional evidence consistent with a mispricing-based interpretation emerges from the behavior of anomaly returns around earnings announcements. Engelberg et al. (2018) show that many anomaly returns are concentrated on earnings announcement days, which they interpret as evidence that anomalies reflect mispricing that is corrected when new information arrives. Consistent with this interpretation, we find that anomalies with high OTP values exhibit substantially stronger earnings-announcement returns than anomalies with medium or low OTP values. This pattern suggests that price corrections around earnings announcements are particularly pronounced for anomalies concentrated among stocks with active option markets.

Beyond relying on external anomaly classifications, we further examine the trading behavior of option investors. Mispricing creates profitable trading opportunities that informed investors may optimally exploit through the options market rather than the equity market (Easley et al., 1998). We therefore study the directional positioning of option end users relative to anomaly signals with different OTP values. Using structurally identified option demand shocks derived from a sign-restricted vector autoregression, we find that anomaly signals with high OTP predict pronounced directional option demand: end users increase call demand and reduce put demand following high realizations of high-OTP anomaly signals. In contrast, signals with low OTP are associated with symmetric increases in call and put demand, consistent with volatility-oriented trading strategies. Taken together, these findings support the interpretation that OTP captures the extent to which an anomaly reflects cross-sectional variation in stock mispricing.

Beyond looking at specific anomaly categories, we further examine how OTP varies with option market characteristics, specifically option type and moneyness. We decompose option trading volume into call and put components and additionally segment volume by moneyness. We find that OTP is present across all option type and moneyness segments but exhibits some noteworthy heterogeneity. For the aggregate anomaly portfolio, estimates are slightly smaller for deep in-the-money and deep out-of-the-money categories (OTP of 0.08) relative to other moneyness segments. Volatility-related anomalies display particularly high OTP values among the out-of-the-money volume category (OTP of 0.36). In contrast, momentum-related anomalies exhibit stronger OTP among the deep in-the-money volume category (OTP of 0.36).

The prevalence of anomaly returns among stocks with high option trading activity raises important questions about the underlying economic mechanisms. One possibility is that the anomaly signal captures cross-sectional variation in mispricing, prompting option market participants to exploit perceived inefficiencies for profit. Alternatively, the anomaly signal may reflect cross-sectional variation in exposures to systematic risks, in which case option traders may engage in trading to hedge underlying risk. In either case, stocks with high option trading activity are likely to be the primary carriers of the anomaly—either because they exhibit stronger mispricing that attracts informed trading, or because they bear greater exposure to the risks captured by the signal.

To diagnose the underlying channel behind the prevalence of anomaly returns among high option volume stocks, we start by comparing OTP to existing anomaly classifications proposed in the literature. These external classifications serve as a valuable benchmark and starting point for assessing the informational content of OTP. First, we document that anomalies with higher OTP tend to exhibit higher unconditional alphas relative to both the CAPM and the three-factor model, suggesting that OTP could be linked to the extend of mispricing captured by a signal.

Second, we calculate OTP separately for anomalies grouped according to the qualitative classifications of Chen et al. (2023), who categorize them according to the original authors' stated rationales. Among the 76 matched anomalies they label as mispricing-based, we observe a significant amplification of returns in high-option-activity stocks: average monthly long-short returns increase from 0.29% (t-statistic of 3.13) to 0.43% (t-statistic of 4.11), yielding an average OTP of 0.14% (t-statistic of 3.22). In contrast, the 24 matched anomalies classified as risk-based exhibit virtually no variation in average returns across option volume quintiles: Monthly returns are at 0.32% both unconditionally and among high option volume stocks, resulting in an OTP of zero.

Third, we further evaluate OTP by comparing it to two additional mispricing classifications: the measures from Bali et al. (2023) and Frey (2023). In the cross-section of anomalies, OTP is strongly positively correlated with Frey's measure, which is based on the predictive power of a signal for revisions in analysts' earnings forecasts. This finding suggests that analysts (and investors) have predictably erroneous expectations about the earnings of stocks with high option trading volume. These stocks are, thus, mispriced and have pronounced returns when the mispricing is corrected.

Finally, we examine anomaly returns around earnings announcements. Engelberg et al. (2018) show that many anomaly returns are highly concentrated on earnings announcement days. While these return patterns could, in principle, reflect heightened risk exposures during periods of elevated firm-specific information flow, the authors argue that they are most consistent with mispricing. Specifically, they suggest that investor expectations are systematically biased, conditional on information from anomaly signals. Earnings announcements then act as correction points where these biases are partially reversed, resulting in price adjustments. We find that high-OTP anomaly portfolios experience average long-short returns of 1.19% on earnings announcement days, compared to 0.24% for medium-OTP anomalies and –0.17% for low-OTP anomalies. This pattern suggests that price adjustments at earnings releases primarily accrue to anomalies concentrated in stocks with high option trading activity.

Beyond relying on mispricing classifications from the literature, we further disentangle mispricing from risk-based explanations by drawing on the idea that mispricings create profitable opportunities, which informed investors may optimally exploit through the options market rather than the equity market (see Easley et al., 1998). To test this, we examine the directional positioning of option end users relative to high-, medium-, and low-OTP anomaly signals. A central challenge in this setting is that option markets are characterized by zero net supply. Consequently, observed option prices and quantities are equilibrium objects that jointly reflect the interaction between end users and market makers. To address this challenge, we estimate a sign-restricted vector autoregression to derive structurally identified call and put option demand shocks at the individual stock level for end users and market makers. We show that anomaly signals with high OTP predict pronounced directional option demand shocks: end users increase call demand and reduce put demand in response to high-OTP signals. In contrast, low-OTP signals are associated with symmetric increases in call and put demand, consistent with volatility-related trading motives. Taken together, these findings support the interpretation that OTP captures the extent to which an anomaly reflects cross-sectional variation in stock mispricing.

Related literature This chapter contributes to a broad literature demonstrating that option markets contain information about future stock returns. Prior research shows that both option prices (e.g., Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Muravyev et al., 2025b) and option trading volume (e.g., Hu, 2014; Pan and Poteshman, 2006) predict future stock returns. Theoretical work by Easley et al. (1998) and Chakravarty et al. (2004) explains this relationship by arguing that investors with private information may prefer to trade in the options market rather than the underlying equity due to the leverage embedded in option contracts. Closely related empirical work examines the informational content of option trading activity. Roll et al. (2010) show that higher option-to-stock trading volume predicts stronger stock returns around earnings announcements. Extending the analysis to the broader cross-section of stocks, Johnson and So (2012) document that option-to-stock volume negatively predicts future stock returns, which they attribute to informed trading on negative information and the avoidance of short-sale constraints. Further evidence by Ge et al. (2016) shows that specific components of option trading activity, such as call purchases opening new positions, are particularly informative. While this literature shows that option trading activity contains valuable information about future returns, it has not examined how option trading activity interacts with a broad set of anomaly signals in the cross-section of expected returns. Our analysis addresses this gap.

This chapter also contributes to the literature that seeks to classify asset pricing anomalies according to whether they reflect risk premia or mispricing. Recent approaches include textual classifications based on the original authors' interpretations (Chen et al., 2023), model-based mispricing measures (Bali et al., 2023), and measures based on analysts' forecast errors (Frey, 2023). Importantly, neither of these measures uses information from the options markets. Our approach complements these methods by providing a market-based diagnostic derived from option trading activity that helps identify which anomalies are most strongly associated with mispricing.

Furthermore, our study contributes to the literature on "smart money" in financial markets. McLean et al. (2020) examine the trading behavior of different investor groups and show that firms and short sellers tend to trade in the profitable direction relative to anomaly signals, whereas retail investors and many institutional investors generally do not. Da et al. (2024) provide evidence that both corporate insiders and outsiders trade in ways that predict future returns, although the predictive effects of insider trades are more persistent. In related work, Hollstein and Wese Simen (2024) analyze option inventories and find that option end users, on average, take positions opposite to those implied by anomaly signals. We extend this line of research by estimating a sign-restricted vector autoregression to identify orthogonal option supply and demand shocks at the individual stock level and by examining whether option end users trade directionally in response to anomaly signals, particularly those associated with high OTP values.

This chapter proceeds as follows. Section 4.2 presents a stylized framework that motivates the interaction between anomaly signals and option trading activity. Section 4.3 describes the data and anomaly signals used in our empirical analyses. Section 4.4 presents the main results on the Option Trading-Implied Prevalence of anomalies. Section 4.5 evaluates whether OTP reflects mispricing or risk-based explanations underlying OTP. Section 4.6 concludes.

4.2 Option Volume and Anomaly Returns

4.2.1 Economic Intuition

This chapter studies why the returns of many asset pricing anomalies are disproportionately concentrated among stocks with high option trading activity. Two economic mechanisms may generate such a pattern.

First, option trading could reflect *hedging demand*. Investors exposed to fluctuations in stock prices may use options to hedge risk. In this case, option trading activity is likely to be higher for stocks with greater return volatility or stronger exposures to systematic risk factors. If an anomaly signal captures cross-sectional variation in risk premia, anomaly returns should therefore be more pronounced among stocks with high option trading activity.

Second, option trading may reflect *speculative trading on mispricing*. Investors who identify mispricing may prefer to trade options because they provide leverage and may be less constrained than equity positions (Easley et al., 1998). Under this interpretation, stocks with larger mispricing attract more option trading activity. If an anomaly signal captures cross-sectional variation in mispricing, anomaly returns should therefore be concentrated among stocks with high option trading activity.

These mechanisms imply that option trading activity may reveal whether the return predictability captured by an anomaly reflects risk exposures or mispricing. The stylized framework developed below formalizes this intuition and illustrates how anomaly returns interact with option trading activity under these two mechanisms.

4.2.2 A Stylized Framework for the Cross-Section of Expected Returns

We consider a one-period setting with two dates, t and $t+1$, and a cross-section of stocks indexed by $i = 1, \ldots, I$. Stock prices may deviate from fundamental values, creating a wedge between the fundamental value $V_{i,t}$ and the traded price $P_{i,t}$. We define mispricing as:

$$M_{i,t} = V_{i,t} - P_{i,t} = \sigma_M \varepsilon_{i,t}^M \tag{4.1}$$

where $\varepsilon_{i,t}^M \sim N(0,1)$, and σ_M governs the cross-sectional variation in mispricing.

At time $t+1$, all firms are liquidated, so that $V_{i,t+1} = P_{i,t+1}$. The fundamental value of stock i evolves according to:

$$V_{i,t+1} = V_{i,t} + RP_{i,t} + \eta_{i,t+1}, \tag{4.2}$$

where $RP_{i,t}$ denotes the risk premium on stock i. We assume a two-factor structure for expected returns. The first factor is common across stocks, while the second factor generates cross-sectional variation in expected returns. Specifically,

$$RP_{i,t} = \lambda_1 + \beta_{2,i}\lambda_2, \tag{4.3}$$

where λ_1 and λ_2 are the market prices of factor risks. The innovation in fundamental value is given by

$$\eta_{i,t+1} = \beta_{i,1}F_{1,t+1} + \beta_{i,2}F_{2,t+1} + \sigma_i \varepsilon_{i,t+1}^P, \tag{4.4}$$

where $\beta_{i,1} = 1$ for all stocks i, $\beta_{i,2}$ varies across stocks with cross-sectional mean zero, and $\varepsilon_{i,t+1}^P$ and the factors are i.i.d. $N(0,1)$-distributed.

Without loss of generality, we normalize $P_{i,t} = 1$, so that the return on stock i can be written as:

$$r_{i,t+1} = P_{i,t+1}/P_{i,t} - 1 = M_{i,t} + RP_{i,t} + \eta_{i,t+1}$$

The *econometrician* does not observe the components $M_{i,t}$ and $RP_{i,t}$ separately, but instead observes a characteristic $C_{a,i,t}$ of anomaly a that is an imperfect signal about expected returns. We model this characteristic as

$$C_{a,i,t} = \phi_a \left(\zeta_a \varepsilon_{i,t}^M + \sqrt{1-\zeta_a^2}\beta_{i,2} \right) + \sqrt{1-\phi_a^2}\varepsilon_{a,i,t}^C, \tag{4.5}$$

where $\varepsilon_{a,i,t}^C \sim N(0,1)$ is a noise term. The parameter $\phi_a \in [0,1]$ captures how informative characteristic C_a is about expected returns, while $\zeta_a \in [0,1]$ determines whether the signal is primarily informative about mispricing or risk premia. When $\zeta_a = 1$, the characteristic reflects only cross-sectional variation in mispricing. When $\zeta_a = 0$, it reflects only cross-sectional variation in risk premia.

In empirical applications, anomaly portfolios are constructed by sorting stocks on such characteristics. The framework therefore captures the possibility that anomaly signals reflect either cross-sectional variation in mispricing or variation in risk premia. In the next subsections, we link these components to option trading activity.

4.2.3 Investors Use Options for Hedging

In this subsection, we assume that investors use options to hedge fluctuations in stock prices between times t and $t+1$. Since all shocks are assumed to be normally distributed, investors can, for example, buy straddles to insure against large price movements. We assume that the option trading volume $OTV_{i,t}$ in options written on stock i at time t reflects the overall hedging demand for that stock. In particular, we assume that option trading activity is proportional to the variance of stock returns:

$$OTV_{i,t} \propto Var_t(r_{i,t+1}) \tag{4.6}$$

Using the return decomposition introduced in Section 4.2.2, return variance can be written

$$Var_t(r_{i,t+1}) = Var_t(F_{1,t+1}) + \beta_{i,2}^2 Var_t(F_{2,t+1}) + \sigma_i^2. \tag{4.7}$$

Under this interpretation, sorting stocks by option trading activity corresponds to a (noisy) sort on the absolute exposure to the second factor F_2. The noise arises from cross-sectional variation in idiosyncratic variance σ_i^2.

Since the risk premium component of returns is affine-linear in $\beta_{i,2}$, stocks with the largest absolute factor exposures, and therefore the highest positive and negative risk premia, will, on average, end up in the portfolio with the highest option trading volume. Under this interpretation, an anomaly is more concentrated among high option volume stocks if the characteristic is informative about the cross-sectional variation in risk premia. Conversely, if the characteristic is informative only about cross-sectional variation in mispricing, it should be independent of $\beta_{i,2}$ and, consequently, independent of option trading volume.

To illustrate the implications of the framework quantitatively, we conduct a simple simulation exercise with the following parameter assumptions: There are $I = 2{,}000$ stocks in the cross-section, and the average risk premia are $\lambda_1 = 0.01$ and $\lambda_2 = 0.01$, corresponding to a monthly horizon. The factor loadings $\beta_{i,2}$ are drawn i.i.d. from a standard normal distribution, as are the mispricing shocks $\varepsilon_{i,t}^M$, with $\sigma_M = 0.01$. Consequently, the predictable component of returns is evenly split between the mispricing and risk premium components.

Idiosyncratic volatility σ_i is drawn from a normal distribution with mean 0.04 and standard deviation 0.01. The factors F_1 and F_2 are drawn i.i.d. from normal distributions with mean zero and standard deviation 0.04. Under these assumptions, a stock with $\beta_{i,2} = 0$ has an annual return volatility of approximately 19.71%, with roughly half of the variation being idiosyncratic.

We consider informative but noisy characteristics with $\phi_a = 0.2$ and study two extreme cases in which the characteristic is either informative only about the risk premium component ($\zeta_a = 0$) or only about the mispricing component ($\zeta_a = 1$) of expected returns. We draw 30,000 panels of returns and characteristics, split into 100 chunks of 300 observations each. For each chunk, we perform dependent double sorts of the 2,000 stocks into 5×5 portfolios: first sorting on OTV and then, within each OTV-quintile, sorting on the simulated characteristic.

Panel A of Table C.1 reports the average returns of the 25 portfolios for the two cases in which the characteristic is informative either about the risk premium component ($\zeta_a = 0$) or the mispricing component ($\zeta_a = 1$). When the characteristic is informative about the risk premium, the return difference between high- and low-characteristic stocks increases with option trading volume. The low OTV quintile primarily contains stocks with small absolute factor exposures β_2, so sorting on a characteristic that captures variation in risk premia ($\zeta_a = 0$) produces larger return spreads in high option volume portfolios.

In contrast, when the characteristic is informative only about the mispricing component ($\zeta_a = 1$), the return spreads are unrelated to option trading volume.

4.2.4 Investors Use Options for Speculation

Unlike in the previous subsection, we now assume that option trading volume reflects the trading activity of sophisticated investors who detect and exploit mispricing.

We assume that investors observe a noisy signal about the fundamental value of stock i:

$$S_{i,t} = V_{i,t} + \sigma^S \varepsilon_{i,t}^S, \tag{4.8}$$

where $\varepsilon_{i,t}^S$ is i.i.d. $N(0,1)$-distributed and represents noise in the private signal. The signal $S_{i,t}$ can be interpreted as a private valuation or analyst estimate of the stock's fundamental value.

Following Easley et al. (1998), we assume that investors choose to trade in the options market to exploit perceived mispricing. Specifically, investors take directional option positions depending on whether they perceive the stock to be undervalued or overvalued. If $S_{i,t} > P_{i,t}$, the stock appears undervalued and investors take bullish option positions, for example by buying calls or selling puts. Conversely, if $S_{i,t} < P_{i,t}$, investors take bearish option positions, such as buying puts or selling calls.

Under this interpretation, the intensity of option trading activity reflects the magnitude of perceived mispricing. We therefore assume that option trading volume satisfies

$$OTV_{i,t} \propto (S_{i,t} - P_{i,t})^2 = (M_{i,t} + \sigma^S \varepsilon^S_{i,t})^2. \tag{4.9}$$

This specification captures the idea that speculative trading activity increases with the magnitude of perceived mispricing, regardless of its direction.

Under this interpretation, sorting stocks by option trading activity tends to concentrate stocks with larger mispricing in the high-volume group. If an anomaly signal captures cross-sectional variation in mispricing, the return spread associated with the anomaly should therefore be larger among stocks with high option trading activity. Conversely, if the characteristic captures only variation in risk premia, the return spreads should be independent of option trading activity.

We again run simulations using the same parameters as in Section 4.2.3, with the additional assumption that σ_S, the volatility of the noise component in the signal, is equal to 0.01, implying a signal-to-noise ratio of 50%. In contrast to the analysis in Section 4.2.3, we now assume that option trading volume reflects speculative activity in the options market, as implied by Equation (4.9).

Panel B of Table C.1 reports the average returns of the 25 portfolios for two cases in which the characteristic is either informative only about the risk premium component ($\zeta_a = 0$) or only about the mispricing component ($\zeta_a = 1$). In the first case, the return difference between high- and low-characteristic stocks is largely unrelated to option trading volume. This occurs because the characteristic reflects only cross-sectional variation in risk premia, whereas option trading activity reflects speculative trading on mispricing.

In contrast, when the characteristic is only informative about the mispricing component ($\zeta_a = 1$), the return difference between high- and low-characteristic stocks increases with option trading volume. In the high-option volume quintile, stocks tend to exhibit larger mispricing, and the characteristic helps distinguish under- and overpriced stocks. In the low-option volume quintile, stocks are more accurately priced, resulting in little variation in expected returns across characteristic-sorted portfolios.

Taken together, the stylized framework highlights that the interaction between anomaly signals and option trading activity depends on the economic mechanism that generates option demand. When option trading reflects hedging of risk exposures, anomaly returns become more pronounced among stocks with high option trading activity if the anomaly signal captures variation in risk premia. In contrast, when option trading reflects speculative trading on mispricing, anomaly returns concentrate among high option volume stocks if the signal captures cross-sectional variation in mispricing.

Motivated by these predictions, the empirical analysis below examines whether anomaly returns are systematically more prevalent among stocks with high option trading activity and evaluates whether anomalies with high OTP values, that is, anomalies whose returns are concentrated among stocks with high option trading activity, exhibit characteristics typically associated with mispricing.

4.3 Data

4.3.1 Optionable Stocks

In our empirical analysis, we adopt the option-to-stock volume ratio (O/S), introduced by Roll et al. (2010), as a readily available measure of options trading activity in the underlying stock. The measure captures the relative intensity of trading in derivative versus underlying markets and has been widely used as a proxy for informed trading in options markets. For a given stock i, $O/S_{i,t}$ is defined as the total trading volume in option contracts written on the stock, irrespective of moneyness or maturity, during calendar month t, divided by the corresponding stock trading volume in shares. Options data are obtained from OptionMetrics Ivy DB database.

In addition to requiring that stocks be optionable, we restrict the sample to common stocks actively traded on the NYSE, AMEX, or Nasdaq. We obtain stock data from the Center for Research in Security Prices (CRSP). Since options data are only available starting in January 1996, the sample period for our portfolio return and OTP analyses begins in February 1996 and extends through July 2021.

In the empirical analysis below, we use the option-to-stock volume ratio (O/S) to sort stocks by the intensity of options trading activity. This sorting allows us to compare anomaly returns among stocks with high options trading activity to those in the broader universe of optionable stocks. The resulting difference forms the basis for the construction of the Option Trading-Implied Prevalence (OTP) measure analyzed in Section 4.4.

4.3.2 Anomaly Signals

We use anomaly signals provided by Chen and Zimmermann (2022) via the website `www.openassetpricing.com/`. To ensure reliable portfolio sorts, we retain only "continuous" anomaly signals, excluding those with a limited number of distinct values, which may lead to distortions in quintile portfolio formation. Additionally, we exclude any signals that incorporate information from the options market to avoid mechanical relationships with our option volume measure. These filters leave us with a set of 278 anomaly signals.

4.3.2.1 Signing

Chen and Zimmermann (2022) provide directional signs for anomaly signals based on the original publications. However, their coverage includes only 197 of the 278 continuous, non-option-based signals, with gaps particularly, though not exclusively, affecting quarterly variants or closely related constructions (e.g., idiosyncratic volatility calculated using the CAPM versus the three-factor model). To avoid manual sign assignment, we implement a heuristic, multi-step procedure based on signal correlations.

In the first step, we compute pairwise correlations between signed and unsigned signals and assign a sign to an unsigned signal if its absolute correlation with a signed counterpart exceeds 0.90. This procedure covers 36 of the 81 initially unsigned signals. In the second step, for each remaining unsigned signal, we identify the three signed signals with the highest absolute correlations. If all three exhibit consistent signs, we infer and assign the same sign to the unsigned signal. This second step resolves an additional 25 cases, yielding a total of 61 signed signals out of the original 81. The remaining 20 signals, which lack consistent directional information among their most correlated peers, are excluded from further analysis. This leaves us with 258 signed anomaly signals.

4.3.2.2 Clusters

Given the large number of anomaly signals, it is not practical to discuss each individually. Instead, we group them based on the similarity of the information they convey. For each month, we compute the cross-sectional ranks of all signals and scale them to the interval $[0, 1]$. We then calculate pairwise correlations of these ranks across our sample of optionable stocks from 1996 to 2021.

To form the clusters, we begin by iterating through all signal pairs, starting with the pair exhibiting the highest correlation and proceeding in descending order. Signals that are highly correlated are generally assigned to the same cluster. Specifically, each signal initially forms its own cluster. During the iteration process, two clusters are merged if all pairwise correlations between signals in the two candidate clusters exceed 0.2. In the second refinement step, we reapply the algorithm using a looser criterion: two clusters are merged if the average correlation between their signals exceeds zero, subject to the constraint that no resulting cluster contains more than 40 signals. The algorithm terminates when a total of 10 clusters have been formed.

We observe that a large number of anomalies related to liquidity and trading volume concentrate within a single cluster. To avoid mechanical overlap with our option-to-stock volume (O/S) measure, we exclude this cluster from further analysis. In addition, we remove all remaining "trading" anomaly signals that appear in other clusters. After applying these filters, we retain a final sample of 221 continuous anomaly signals that are neither based on options data nor directly related to trading activity, and which span the remaining nine clusters.

While alternative parameterizations of the clustering algorithm yield marginally different groupings, our goal is not to identify a unique optimal partition but rather to impose economic structure on a high-dimensional signal space. This approach allows us to interpret patterns in anomaly returns through a smaller number of economically meaningful categories. The resulting clusters are stable across specifications and provide a practical framework for evaluating how different sources of return predictability interact with options market activity. The resulting clusters, along with descriptions of the anomaly signals used in our study, are presented in Table C.2. We label the clusters according to their dominant informational theme: *Accruals*, *Intangibles*, *Investment*, *Issuance*, *Momentum*, *Profitability*, *Risk*, *Value*, and *Volatility*.

4.4 Option Trading-Implied Prevalence of Anomalies

In order to measure the *Option Trading-Implied Prevalence* (OTP) of a given anomaly signal, we first sort stocks into quintiles based on their option-to-stock trading volume (O/S), measured in the previous month. Within each O/S quintile, we then independently sort stocks into five portfolios based on the respective anomaly signal, also lagged by one month. We compute the long-short anomaly return within the highest O/S quintile and compare it to the unconditional long-short anomaly return across all optionable stocks. We define OTP as the difference between these two returns. Formally, for anomaly signal a, we define

$$OTP_a = R^{LS}_{a,\,Q5(O/S)} - R^{LS}_a, \tag{4.10}$$

where $R^{LS}_{a,\,Q5(O/S)}$ denotes the long-short return of anomaly a among stocks in the highest O/S quintile and R^{LS}_a denotes the unconditional long-short anomaly return across all optionable stocks. A positive OTP_a therefore indicates that the return associated with anomaly a is disproportionately concentrated among stocks with elevated option trading activity.

4.4.1 The Aggregate Anomaly Portfolio

To assess whether anomaly returns are systematically concentrated among stocks with active options markets, we begin by examining the aggregate anomaly portfolio, which pools all anomaly signals considered in our study. Table C.3 shows that the unconditional long-short return across all optionable stocks is 0.29% per month, with a t-statistic of 4.18, confirming that, on average, the anomaly signals we consider deliver positive returns in the cross-section. When restricting the sample to stocks in the highest option-to-stock volume quintile, the long-short return increases to 0.40%, with a t-statistic of 5.03. The resulting OTP, defined as the difference between these two returns, is 0.11% per month and statistically significant, with a t-statistic of 3.84. The positive OTP implies that anomaly returns are systematically stronger among stocks with elevated option trading activity.

4.4.2 Anomaly Cluster Portfolios

To better understand how OTP varies across different types of anomaly signals, we examine the cluster-level results reported in Table C.3. We find substantial heterogeneity in OTP across anomaly categories, with volatility, momentum, profitability, and issuance signals exhibiting the strongest prevalence effects.

Volatility-related anomalies show the strongest concentration effect, with an OTP of 0.35% and a t-statistic of 3.03, despite exhibiting only a modest unconditional return of 0.11%. For instance, the idiosyncratic volatility anomaly signal *idiovol3f* delivers an OTP of 0.75% (t-statistic of 3.65, see Table C.2), indicating particularly strong effects among stocks with high option trading activity.

Momentum and profitability anomalies also display elevated OTP values of 0.30% (t-statistic of 3.37) and 0.29% (t-statistic of 2.73), respectively. A notable example in the momentum cluster is the 12-month momentum signal *mom12m*, which exhibits an unconditional effect size of only 0.45% among optionable stocks, but rises to 1.20% in the high-O/S quintile (t-statistic of 2.80). The resulting OTP of 0.75% (t-statistic of 2.75) reflects strong anomaly prevalence in this group. Similarly, the profitability signal cash-based operating profitability *cboperprof* exhibits an OTP of 0.56% (t-statistic of 3.08).

Issuance and investment anomalies follow with OTP values of 0.22% (t-statistic of 2.87) and 0.10% (t-statistic of 1.92), respectively. An example in the issuance cluster is *netpayoutyield*, which shows a pronounced concentration effect with an OTP of 0.45% (t-statistic of 2.99). In contrast, the anomaly *investment*, a representative of the investment cluster, only exhibits an OTP of 0.03% (t-statistic of 0.21).

By contrast, clusters related to accruals, risk, intangibles, and value exhibit much lower or even negative OTP values. For example, the risk cluster has an OTP of -0.01% with a statistically insignificant t-statistic of -0.09. A prominent example within this cluster is the *beta* anomaly, which shows an OTP of -0.52% (t-statistic of -3.02), indicating that among high option volume stocks, high-beta stocks earn lower returns relative to low-beta stocks. This pattern may already indicate that positive OTP values are not associated with risk-based anomalies and, in the context of our framework from Section 4.2, that option volume does not reflect anomaly prevalence because of hedging motives. We analyze this risk-versus-mispricing distinction more thoroughly in the subsequent section.

Value-related anomalies yield an OTP of -0.18%, marginally significant with a t-statistic of -1.67. Notably, the classic quarterly book-to-market ratio bmq exhibits a negative OTP of -0.75% (t-statistic of -3.57), indicating that value effects tend to weaken or even reverse among stocks with high option activity. This finding may relate to the documented "value decline", i.e., the strong relative performance of growth stocks in recent years (see Eisfeldt et al., 2020; Gonçalves and Leonard, 2023).

4.4.3 OTP and Effect Size

A potential concern regarding the interpretation of OTP is that variation across anomalies may merely reflect variation in anomaly strength. In our model, when ϕ_a, that is, the information content of the anomaly signal, is very low, neither a sort on high option volume stocks nor an unconditional sort yields economically meaningful return differences. In this case, in equation (4.10), both $[R^{LS}_{a,Q5(O/S)}]$ and $[R^{LS}_a]$, and thus also OTP_a, are close to zero.

On the other hand, one might expect a negative relationship between the estimated OTP_a and the estimated $[R^{LS}_a]$, since the latter directly enters the definition of OTP_a with a negative sign. Ultimately, the cross-signal relationship between OTP_a and $[R^{LS}_a]$ is an empirical question. Figure C.1 shows that, in our sample, this relationship is estimated to be only very weak. Both OTP and the unconditional effect size vary roughly between -0.5% and 1% per month, but there is no clustering of anomaly signals along the 45-degree line, as would be expected under a mechanical relationship. In conclusion, OTP indeed captures a distinct property of an anomaly relative to the unconditional effect size.

4.4.4 Stock Volume and OTP

Han et al. (2022) show that mispricing is amplified among stocks with high trading volume, raising the concern that the variation in anomaly returns across O/S segments could reflect differences in underlying stock trading volume rather than option market activity per se. Because stock volume enters the denominator of the option-to-stock volume ratio, it is important to verify that our results are not driven by stock trading volume effects.

To address this concern, we adjust our OTP estimates for stock trading volume using a dependent triple-sort. Specifically, we first sort stocks into quintiles based on stock trading volume.

Within each stock-volume quintile, stocks are then sorted into quintiles based on the option-to-stock volume ratio. Within each (stock volume, O/S) cell, we subsequently sort stocks into quintiles based on the anomaly signal. Importantly, anomaly portfolio returns within the O/S quintiles are first averaged across stock-volume quintiles at the portfolio level, thereby equalizing the stock-volume composition among O/S portfolios. The adjusted long–short return is then computed from these stock-volume-averaged portfolios. Appendix Table C.6 reports the corresponding results.

Reassuringly, the estimated adjusted OTP values remain very similar in magnitude and statistical significance to our baseline estimates across most anomaly clusters. In particular, volatility, momentum, profitability, and issuance anomalies continue to exhibit strong prevalence among high option volume stocks even after adjusting for stock volume. For example, the adjusted OTP equals 0.30% for momentum (t-statistic of 3.91) and volatility (t-statistic of 2.50), 0.28% for profitability (t-statistic of 3.00), and 0.23 percentage points for issuance (t-statistic of 3.14). These results suggest that the concentration of anomaly returns documented above is not driven by stock trading activity, but instead reflects information contained in option trading volume beyond what is captured by equity market volume alone.

4.4.5 Option Volume by Type and Moneyness

To better understand which types of option trades are associated with the documented anomaly prevalence, we decompose option trading activity by option type and moneyness. We first decompose the option-to-stock volume ratio into its call-to-stock volume (C/S) and put-to-stock volume (P/S) components. We recalculate OTP values based on these components and report the results in Appendix Table C.7. The findings are largely consistent with those based on total option volume. In particular, anomalies related to volatility, momentum, profitability, and issuance exhibit high OTP values across both call- and put-based specifications. This evidence suggests that the documented anomaly prevalence among high option volume stocks is not driven by a single option type. Magnitudes are slightly higher when conditioning on put volume, most notably for the profitability cluster (OTP of 0.37%) and the value cluster, which shows a highly negative OTP of -0.45%.

In Table C.7 we also report results separately for the long and short legs of the anomaly portfolios. Across volume definitions, the concentration of anomaly returns among high option volume stocks is primarily driven by the low-return leg. In particular, OTP_S is negative and statistically significant across most anomaly clusters, indicating that stocks in the short leg earn substantially lower returns when option trading activity is high. In contrast, OTP_L is generally smaller in magnitude, suggesting that high option volume is less strongly associated with higher returns of the long leg. This pattern indicates that the stronger anomaly returns among high option volume stocks are primarily driven by the particularly poor performance of stocks with unfavorable anomaly signals.

We next examine which moneyness segments of option trading volume drive the concentration of anomaly returns. We define moneyness segments following Bollen and Whaley (2004), based on option delta from OptionMetrics.[10] Focusing on total option volume and the aggregate OTP measure, Table C.8 shows that the effect is present across moneyness categories but varies across anomaly clusters. For the aggregate anomaly portfolio, OTP is positive and statistically significant for option volumes of all moneyness categories, with estimates that are largest for OTM and ATM contracts (OTP of 0.10) and only slightly smaller for deep in-the-money options (OTP of 0.08).

The heterogeneity becomes more pronounced at the cluster level. In particular, volatility anomalies exhibit especially large and statistically significant OTP values for OTM volume (OTP of 0.36). In contrast, momentum anomalies display relatively stronger OTP for in-the-money or even deep in-the-money volume (OTP of 0.36), suggesting that option trading related to momentum signals relies more heavily on contracts with higher exposure to the underlying. Overall, these results indicate that the documented anomaly prevalence among high option volume stocks is not driven by a single moneyness segment. At the same time, the observed variation across anomaly clusters may point to distinct option trading strategies associated with different types of anomaly signals.

While anomaly returns are, on average, more prevalent among high-option-volume stocks, the results in this section highlight pronounced heterogeneity across anomaly types. In particular, signals related to volatility, momentum, profitability, and issuance exhibit strong prevalence effects. Investment anomalies show more moderate effects, whereas categories such as accruals, risk, intangibles, and value display weak or even negative patterns. In the next section, we investigate whether this heterogeneity is related to differences in the underlying economic nature of these anomalies.

4.5 Anomaly Prevalence: Mispricing or Risk?

In Section 4.2, we introduced a stylized framework suggesting that the prevalence of anomaly returns among stocks with high option trading volume can arise through two main channels. First, anomaly signals may capture cross-sectional differences in risk premia, in which case

[10]For call options, contracts with delta greater than 0.875 are classified as deep-in-the-money (DITM), 0.625 to 0.875 as in-the-money (ITM), 0.375 to 0.625 as at-the-money (ATM), 0.125 to 0.375 as out-of-the-money (OTM), and ≤ 0.125 as deep-out-of-the-money (DOTM). For put options, we apply the symmetric classification using negative delta thresholds: > -0.125 (DOTM), -0.375 to -0.125 (OTM), -0.625 to -0.375 (ATM), -0.875 to -0.625 (ITM), and ≤ -0.875 (DITM).

option trading activity reflects hedging demand associated with these risks. Second, anomaly signals may reflect cross-sectional variation in mispricing, in which case option traders may actively take positions to exploit perceived inefficiencies. Under either channel, stocks with elevated option trading activity may disproportionately carry anomaly returns—either because they exhibit stronger mispricing that attracts informed trading or because they exhibit greater exposure to priced risks that motivates hedging. In this section, we empirically examine which of these mechanisms is most consistent with the observed option trading-implied prevalence of anomaly returns.

4.5.1 Relation with Other Anomaly Classifications

We begin by comparing OTP with existing anomaly classifications proposed in the literature. These external classifications provide a valuable benchmark for assessing whether OTP is systematically related to anomaly signals that are commonly interpreted as reflecting mispricing rather than risk premia.

4.5.1.1 Alphas

The most widely used measure of mispricing in the asset pricing literature is a strategy's alpha relative to a factor model. Under the assumption that the employed factors span the stochastic discount factor (or its projection on the set of tradable assets), the alpha quantifies the (short-term) difference between the fair and the observed average rate of return.

We compare each anomaly's OTP to its unconditional, full sample alpha estimated using both the CAPM and the Fama and French (1993) three-factor model. Factor data are obtained from the data library of Kenneth R. French. For each anomaly, we construct univariate quintile long-short portfolios over our sample period (February 1996 to July 2021) and estimate the corresponding alphas. Figure C.2 plots anomaly alphas against their OTP values together with fitted regression lines. We observe positive relationships between the anomaly alphas and OTP under both factor models, indicating that anomalies with higher OTP tend to exhibit larger unconditional alphas.

This comparison provides an initial plausibility check: anomalies with higher alphas also tend to exhibit higher OTP values, suggesting a potential link between mispricing and the concentration of anomaly returns in high option volume stocks. However, this relationship should be interpreted with caution. Alpha is not a definitive measure of mispricing, as it may also reflect compensation for omitted risk factors. Moreover, both alpha and OTP are inherently tied to the magnitude of anomaly returns. Anomalies that do not generate economically meaningful return differences, either unconditionally or within high option volume stocks, will exhibit near-zero values for both metrics. As a result, the observed correlation may partly reflect a selection effect: only anomalies with economically significant returns can meaningfully vary in both alpha and OTP. This limitation motivates the use of alternative classifications that more directly distinguish between risk-based and mispricing-based anomalies.

4.5.1.2 Classification by Original Authors

Chen et al. (2023) classify anomaly signals according to whether the original authors interpret them as reflecting mispricing- or risk-based mechanisms. We match 143 of the anomaly signals used in our analysis to their classification and identify 76 as mispricing-based and 24 as risk-based. The remaining 43 are not explicitly labeled by the original authors and are therefore categorized as agnostic.

Panel A of Table C.4 reports results for the 76 anomalies classified as mispricing-based. These signals yield an average unconditional monthly long-short return of 0.29% (t-statistic of 3.13) across optionable stocks. Among stocks with high options trading activity, the return increases to 0.43% (t-statistic of 4.11), resulting in a statistically significant average OTP of 0.14% (t-statistic = 3.22), or roughly half the unconditional return.

Panel B of Table C.4 presents results for the 24 anomalies classified as risk-based. These signals generate an average monthly return of 0.32% (t-statistic of 3.64) among optionable stocks, which remains essentially unchanged in the high-O/S group (t-statistic of 3.27), implying an average OTP close to zero.

Panel C of Table C.4 presents the results for 43 agnostic anomalies that are not classified as either risk-based or mispricing-based. On average, these anomalies yield a monthly long-short return of 0.34% (t-statistic of 3.29) among all optionable stocks. Among high-O/S stocks, the return increases to 0.44% (t-statistic of 3.74), resulting in a moderate OTP of 0.09 (t-statistic of 2.32) which lies between the OTP of risk-based and mispricing-based anomalies.

Taken together, these results indicate that anomaly signals classified as mispricing-based exhibit substantially higher OTP values than signals interpreted as reflecting risk premia.

4.5.1.3 Alternative Classifications

We further assess the informational content of OTP by comparing it with recent mispricing classifications proposed in the literature. Firstly, we consider the mispricing measure introduced by Bali et al. (2023, hereafter referred to as BBW), which defines mispricing as the deviation of a stock's return from the fair rate of return implied by an IPCA model. Secondly, we draw on Frey (2023, hereafter referred to as $Frey$), who uses earnings forecast errors to link anomalies to biased expectations and mispricing. For completeness, we also revisit the classification by Chen et al. (2023, hereafter referred to as CLZ), which labels anomalies based on the original authors' statements.

We match these external classifications to the anomalies in our sample, yielding 116 matches for BBW, 143 for $Frey$, and 143 for CLZ. From CLZ, we exclude 43 anomalies categorized as 'agnostic', leaving 100 with a clear mispricing or risk-based label. Of the matched sets, BBW classify 35 anomalies as mispricing-based, $Frey$ 59, and CLZ 76.

For each anomaly, we construct a dummy variable indicating whether it is classified as mispricing-based and estimate a logistic model of this indicator on OTP. The fitted values represent the probability that an anomaly is considered mispricing-based conditional on its OTP. Figure C.3 shows the results.

We find that OTP aligns well with the classifications of CLZ and $Frey$: anomalies with high OTP are more likely to be labeled mispricing-based. For example, under the $Frey$ classification, the predicted probability of mispricing rises from around 15% at low OTP values to around 80% at high OTP values. A similar pattern emerges for CLZ, where the predicted probability rises from around 50% to nearly 100%.

In contrast, the association with the BBW classification is weaker and relatively flat. This difference likely reflects methodological differences: BBW is based on a structural asset pricing model, whereas OTP, $Frey$, and CLZ are more directly connected to investor behavior and how information is processed in markets.

Overall, the strongest alignment is with $Frey$, whose measure captures the extent to which a signal cross-sectionally predicts analyst forecast errors, implying that investors fail to fully incorporate available information. This interpretation matches the theoretical channel outlined in Section 4.2, where option traders exploit mispricing. Thus, Frey's measure is directly economically linked to the *speculation*-based interpretation of OTP developed in our framework.

4.5.1.4 Earnings Announcement Returns

Engelberg et al. (2018) show that a substantial portion of anomaly returns occurs around earnings announcement days. While this pattern could be attributed to risk-based explanations, such as elevated factor loadings during periods of firm-specific news, the authors provide compelling evidence supporting a mispricing-based interpretation. They argue that investor expectations are systematically biased, leading to excessive optimism or pessimism toward stocks associated with certain anomalies. Earnings announcements then act as correction points, revealing fundamental information and triggering price adjustments. Consequently, anomalies associated with mispricing tend to exhibit stronger return reactions around earnings announcements.

To examine whether OTP captures variation consistent with this mechanism, we partition anomaly signals into three groups based on their OTP values. Specifically, we assign the bottom 30% of signals to the low-OTP group, the middle 40% to the middle group, and the top 30% to the high-OTP group. Following Engelberg et al. (2018), we construct $NET_{i,t}$ for each stock-month observation within each of our three anomaly groups. $NET_{i,t}$ is defined as the difference between the number of long-side and short-side anomaly portfolios to which a given stock i belongs in a given month t: $NET_{i,t} = Long_{i,t} - Short_{i,t}$. A higher $NET_{i,t}$ indicates that a stock is sorted into relatively more long than short anomaly portfolios, according to the considered group of anomaly signals. We compute this measure separately for each OTP-based anomaly group, resulting in $NET_{i,t}^{high}$, $NET_{i,t}^{middle}$, and $NET_{i,t}^{low}$.

Next, we obtain earnings announcement dates and announcement times from the Institutional Brokers' Estimate System (I/B/E/S) dataset.[11] We then merge these announcement dates with our daily optionable stock data. For each announcement day, we sort stocks into deciles based on their $NET_{i,t}^{high}$, $NET_{i,t}^{middle}$, and $NET_{i,t}^{low}$ and compute daily, pooled long-short returns for each group over an 11-day event window (five days before to five days after an earnings announcement day). Figure C.4 depicts the results.

We find that anomalies with high OTP values exhibit markedly stronger returns on earnings announcement days. High-OTP anomalies generate an average return of 1.19% on announcement days, compared to 0.24% for medium-OTP anomalies and –0.17% for low-OTP anomalies. These results indicate a strong relation between OTP and earnings announcement returns: the announcement-day return patterns documented by Engelberg et al. (2018) are concentrated among anomalies with high OTP, whereas anomalies with moderate or low OTP exhibit little or no announcement-day return reaction. Because earnings announcements represent events where new fundamental information becomes available, this pattern is consistent with interpreting OTP as capturing the extent to which anomaly signals reflect mispricing.

4.5.2 Directional Positioning of Option Traders

To further separate mispricing-based explanations from risk-based ones, we examine the trading behavior of option investors. If high OTP values reflect mispricing, then informed investors should respond by taking *directional* positions, i.e. positions that benefit from expected price movements in the underlying stocks. This idea follows Easley et al. (1998), who show that

[11] When announcements occur after market close but before the next trading day, we shift the announcement date to the following day.

informed traders often prefer to express their views through options due to superior leverage and fewer short-sale constraints compared to stocks.

As discussed in Section 4.2, the interpretation of OTP as a mispricing measure implies that options are used for speculation. Under this interpretation, traders take directional option positions that benefit from expected price movements in the underlying stock: for example, buying calls or selling puts when expecting price increases, and buying puts or selling calls when expecting price declines.

In this section, we test whether directional option trading is systematically related to anomaly signals with high OTP. A central challenge in this setting is that option markets are characterized by zero net supply. As a result, observed option prices and quantities reflect equilibrium outcomes that are jointly determined by the interaction of end users and market makers. In such an environment, measures such as inventories or option prices alone cannot be interpreted as demand, as they may capture either shifts in demand or movements along the opposing side's supply curve.

4.5.2.1 Estimation of Structural Demand Shocks

To adress this identification problem, we estimate *structurally identified option demand shocks* for end users and market makers. These shocks isolate exogenous shifts in demand that are orthogonal to contemporaneous price adjustments and counterparty supply responses, allowing us to directly test whether traders take directional option positions in response to anomaly signals with different levels of OTP.

Our identification strategy exploits information from both quantities and prices in option markets. On the quantity side, we use delta-weighted option inventories constructed from open-close transaction data across major U.S. option exchanges, including the International Securities Exchange (ISE), Chicago Board Options Exchange (CBOE), Nasdaq Options Trade Outline (NOTO), PHLX Options Trade Outline (PHOTO), and ISE Gemini. Following Almeida and Freire (2023), we define option end users as the combined group of *Customers*, *Professional Customers*, and *Firms*. Transaction volumes are aggregated across exchanges and converted into stock-day level delta-weighted call and put inventories using option deltas from OptionMetrics.

On the price side, we use semivariance premia, following Kilic and Shaliastovich (2019) and Held et al. (2020), as measures of the expensiveness of call and put options. Upper (lower) semivariance premia capture the difference between option-implied variance extracted from call (put) options and the ex-ante variance in the positive (negative) return domain under the physical measure. High semivariance premia therefore indicate that calls or puts are expensive relative to the characteristics of the underlying stock, particularly its return variance. Details are provided in Appendix C.3.2.

We combine these price and quantity measures in a sign-restricted vector autoregression (SVAR) framework, following Jacobs et al. (2026) and related applications in financial markets (e.g., Goldberg and Nozawa, 2021). The identifying restrictions exploit the zero–net-supply nature of option markets. A positive end-user demand shock raises both option prices and quantities. In contrast, a positive market maker demand shock raises prices while reducing equilibrium quantities. These particular price–quantity responses form the basis of our sign restrictions.

Structural identification is achieved by retaining only those decompositions consistent with the imposed sign restrictions. We implement a Bayesian estimation procedure to account for parameter uncertainty and follow the median-target approach of Fry and Pagan (2011) to select a unique structural model. Appendix C.3.2 provides a self-contained description of the data construction, the SVAR framework, and the identifying restrictions used in this chapter.

4.5.2.2 Structural Demand Shocks and OTP

Using the resulting structural shocks, we test whether directional option demand is systematically related to anomaly signals with different levels of OTP. Specifically, we regress daily end-user and market maker demand shocks for call and put options on lagged anomaly signals sorted into high, middle, and low OTP buckets. If high-OTP signals are informative about stock mispricing, we expect them to predict directional end-user demand for options. Conversely, under a risk-based interpretation of OTP, such systematic directional demand patterns should be absent. We estimate the following panel regression:

$$Shock_{i,t} = \beta^{high} NET^{high}_{i,t-1} + \beta^{middle} NET^{middle}_{i,t-1} + \beta^{low} NET^{low}_{i,t-1} + \delta_t + u_i + \varepsilon_{i,t}, \qquad (4.11)$$

where $Shock_{i,t}$ denotes the daily structural demand shock of either option end users or market makers for calls or puts on stock i at date t. $NET^{high}_{i,t-1}$, $NET^{middle}_{i,t-1}$, and $NET^{low}_{i,t-1}$ are lagged composite anomaly signals constructed from non-overlapping subsets of characteristics in the high, middle, and low OTP terciles, respectively. Cross-sectional correlations between these composite signals are moderate, with an average correlation of 0.26 between $NET^{high}_{i,t}$ and $NET^{middle}_{i,t}$, –0.34 between $NET^{high}_{i,t}$ and $NET^{low}_{i,t}$, and 0.29 between $NET^{middle}_{i,t}$ and $NET^{low}_{i,t}$. All specifications include time fixed effects (δ_t), and selected columns additionally include stock fixed effects (u_i). Standard errors are double clustered by firm and date.

Panel A of Table C.5 reports the results for option end-user demand shocks. We begin with the high-OTP signals. The coefficients on $NET^{high}_{i,t-1}$ reveal an economically intuitive pattern of directional trading. For call options, $NET^{high}_{i,t-1}$ loads positively and is highly statistically significant, with coefficients of 0.05 (t-statistic of 6.13) without stock fixed effects and 0.09 (t-statistic of 7.15) with stock fixed effects. In contrast, for put options the coefficient is significantly negative at –0.06 (t-statistic of –6.45) and –0.22 (t-statistic of –17.06), respectively.

These estimates imply that option end users increase call demand and reduce put demand for stocks with high realizations of high-OTP anomaly signals relative to stocks with low realizations of high-OTP anomaly signals, consistent with directional trading in line with these anomaly signals.

In contrast, the coefficients on $NET^{middle}_{i,t-1}$ are generally economically weaker. For call options, the estimated coefficients are close to zero and statistically insignificant across specifications. For put options, the coefficient is modestly positive at 0.02 (t-statistic of 1.94) without stock fixed effects and 0.06 (t-statistic of 5.54) with stock fixed effects. While statistically significant in the latter case, the magnitudes are small and the signs are not consistently aligned with a clear directional trading motive. Overall, anomaly signals with intermediate OTP levels do not appear to predict systematic directional option demand.

A different pattern emerges for low-OTP signals. The coefficients on $NET^{low}_{i,t-1}$ are positive and statistically significant for both call and put demand shocks. For calls, the estimates range from 0.02 (t-statistic of 1.81) to 0.03 (t-statistic of 1.86), while for puts they are substantially larger at 0.12 (t-statistic of 10.52) and 0.21 (t-statistic of 12.28). This symmetric increase in demand across option types is indicative of volatility-oriented trading, such as straddle or strangle positions, rather than directional bets on the underlying stock. These results suggest that low-OTP anomaly signals are associated with demand for exposure to return variance rather than expected price movements.

Panel B reports the corresponding results for market maker demand shocks. The estimated coefficients display patterns that closely mirror those for end-user demand shocks. For high-OTP signals, the coefficient on $NET^{high}_{i,t-1}$ is positive and highly significant for call options (0.04 with a t-statistic of 4.61 without stock fixed effects and 0.06 with a t-statistic of 4.69 with stock fixed effects). Since a positive market maker demand shock corresponds to a reduction in equilibrium quantity, these estimates indicate that market makers reduce call supply for stocks with high realizations of high-OTP signals relative to those with low realizations. For put options, in contrast, $NET^{high}_{i,t-1}$ loads significantly negatively (–0.04 with a t-statistic of –5.03 and –0.24 with a t-statistic of –18.97), indicating that market makers reduce put supply for stocks with low realizations of high-OTP signals relative to stocks with high realizations of high-OTP signals.

Coefficients on $NET^{middle}_{i,t-1}$ are generally small and economically weak, mirroring the lack of a clear pattern in end-user demand shocks.

For low-OTP signals, $NET^{low}_{i,t-1}$ loads positively and significantly for both calls and puts, with coefficients ranging from 0.04 to 0.08 for calls and from 0.09 to 0.12 for puts. These estimates imply that market makers reduce supply on both sides of the option market for stocks with high realizations of low-OTP signals.

Taken together, the results provide strong evidence consistent with interpreting OTP as a measure of how informative anomaly signals are about stock mispricing. High-OTP signals are associated with pronounced directional option demand by end users, consistent with informed traders taking positions that exploit perceived mispricing. In contrast, low-OTP signals primarily predict demand shocks that are consistent with volatility-driven trading motives. This cross-sectional heterogeneity in trading behavior aligns closely with the theoretical predictions in Section 4.2 and reinforces the view that OTP distinguishes between anomalies driven by mispricing and those reflecting underlying risk premia.

4.6 Conclusion

This chapter presents new evidence on the interaction between cross-sectional return anomalies and stock-level option trading activity. We document that many well-known anomaly signals—especially those related to momentum, volatility, and profitability—are disproportionately concentrated among stocks with high option trading volume. To systematically quantify this phenomenon, we propose a return-based measure called the *Option Trading-Implied Prevalence* (OTP), designed to capture the degree to which a given anomaly is prevalent among stocks with high levels of option trading activity.

Consistent with a mispricing-based interpretation of our findings, we show that OTP aligns closely with established mispricing classifications of anomalies. Moreover, anomalies with high OTP values also exhibit significantly stronger returns around earnings announcements, indicating that price corrections on earnings announcement days are most pronounced for anomalies that are concentrated among stocks with active option markets.

We further document that OTP meaningfully predicts the directional positioning of option end users. High-OTP anomaly signals are associated with increased call demand and reduced put demand, indicating that informed traders systematically take directional positions consistent with these anomaly signals. In contrast, low-OTP signals primarily predict symmetric demand for calls and puts, consistent with volatility-oriented trading.

Taken together, these results provide a novel, market-based framework for assessing the informativeness of anomaly signals. Across multiple empirical settings, including return concentration, comparisons with existing anomaly classifications, earnings announcement reactions, and directional option demand, we find consistent evidence that option trading activity contains information about the degree to which anomaly signals reflect cross-sectional variation in mispricing. In this sense, OTP provides a new diagnostic measure for distinguishing between anomalies driven by mispricing and those reflecting underlying risk premia.

Chapter 5

Summary and Outlook

This dissertation develops an options-market perspective on the origins of asset pricing anomalies. It asks whether the broad set of cross-sectional return predictors documented in the empirical asset pricing literature reflects compensation for systematic risk or the correction of mispricing, and it leverages information contained in derivative markets—the availability of listed options, the prices at which they trade, and the volume with which they are traded—to shed new light on this longstanding debate. Taken together, the findings demonstrate that options markets provide economically interpretable diagnostics about the nature of stock return anomalies and offer information that complements evidence drawn from the underlying equity market alone.

Chapter 2 begins by examining whether the mere availability of listed equity options is associated with the strength of anomaly returns. Unconditionally, anomalies are substantially more pronounced among stocks without traded options. Yet, for the average anomaly, this difference largely vanishes once size and liquidity differences between optionable and non-optionable stocks are accounted for through a bootstrap matching procedure. The results therefore suggest that the existence of an options market does not affect average anomaly returns. However, beneath this aggregate finding, considerable heterogeneity emerges. Momentum and value anomalies remain stronger among non-optionable stocks even after adjusting for differences in size and liquidity, consistent with the importance of short-selling and information frictions, whereas investment anomalies are stronger among optionable stocks, in line with options alleviating funding frictions and making firms' investment decisions more informative about their cost of capital. Rather than operating through a single channel, optionability appears to affect anomaly returns through multiple, economically distinct mechanisms.

Having established that the presence of options matters in nuanced ways, Chapter 3 turns to the information embedded in option prices themselves. Building on demand-based option pricing theory, the chapter exploits the idea that investor demand can affect option prices because market makers cannot perfectly hedge the risks they absorb. By comparing option-implied synthetic stock prices with the corresponding underlying stock prices, the chapter infers the direction and intensity of investor demand for option-based stock exposure. Relating these price differences to a comprehensive set of anomaly signals reveals that option traders, on average, take positions consistent with the profitable direction implied by cross-sectional return predictors, suggesting that the options market serves as a venue through which sophisticated investors actively exploit stock return predictability. At the same time, substantial differences emerge across anomaly categories. Option traders systematically position themselves on the profitable side of momentum, volatility, profitability, and issuance anomalies, while exhibiting weaker or even opposing positioning with respect to value, beta, and liquidity signals. Moreover, discrepancies between option-implied synthetic stock prices and the corresponding underlying stock prices are strongest when intermediary capital constraints are binding, supporting the view that limited risk-bearing capacity among large financial intermediaries contributes to the persistence of anomaly returns.

Building on this insight, Chapter 4 takes a final step by focusing on option trading activity itself. The chapter shows that anomaly returns are disproportionately concentrated among stocks with high option trading volume and introduces the Option Trading-Implied Prevalence as a novel return-based diagnostic for measuring this concentration. The proposed measure aligns closely with existing anomaly mispricing classifications, is associated with pronounced return reactions around earnings announcements, and predicts directional option demand by end users in a manner consistent with informed trading on mispricing. By contrast, signals for which the measure is low are accompanied by increases in both call and put demand, a pattern more consistent with volatility-oriented trading motives. These findings establish Option Trading-Implied Prevalence as a market-based indicator of the extent to which an anomaly reflects mispricing rather than compensation for risk. Across anomaly categories, the evidence reinforces the conclusions drawn from the preceding chapters: momentum, volatility, profitability, and issuance anomalies appear most consistent with a mispricing-based interpretation, whereas value, risk, and intangibles-related signals seem to be driven by different economic forces.

Viewed together, the three chapters reveal a coherent progression. The presence of traded options shapes anomaly returns through several distinct friction channels, option prices reveal how sophisticated investors position themselves with respect to these anomalies, and option trading activity identifies where mispricing is most likely to be concentrated. Although each chapter approaches the question from a different angle, the evidence converges on a consistent pattern: momentum, volatility, profitability, and issuance anomalies exhibit characteristics most compatible with a mispricing-based interpretation, whereas value, risk, and intangibles-related anomalies appear to be driven by different economic mechanisms. More broadly, the results demonstrate that derivative markets contain valuable information about the economic origins of cross-sectional return predictability that is not readily observable from stock market data alone.

Several promising avenues for future research emerge from these findings. Identifying the investors behind the documented demand pressure in options markets remains an important open question that could be addressed using more granular trader-level data. More broadly, while the analyses in this dissertation focus on equity anomalies and U.S. listed options, the underlying methodological insight—that derivative market characteristics can serve as diagnostics for the sources of return predictability—is readily transferable to other settings. Extending the proposed measures to other asset classes, including corporate bonds, currencies, and commodities, as well as combining them with identification strategies for informed trading, represents a particularly fruitful direction for future work.

Appendix A

Anomalies and Optionability

This appendix presents the main figures and tables associated with Chapter 2. Section A.1 contains the figures, while Section A.2 reports the corresponding tables. In addition, Section A.3 provides additional figures, including a graphical representation of the bootstrap matching procedure, and describes the procedure in greater detail.

A.1 Figures

Figure A.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.

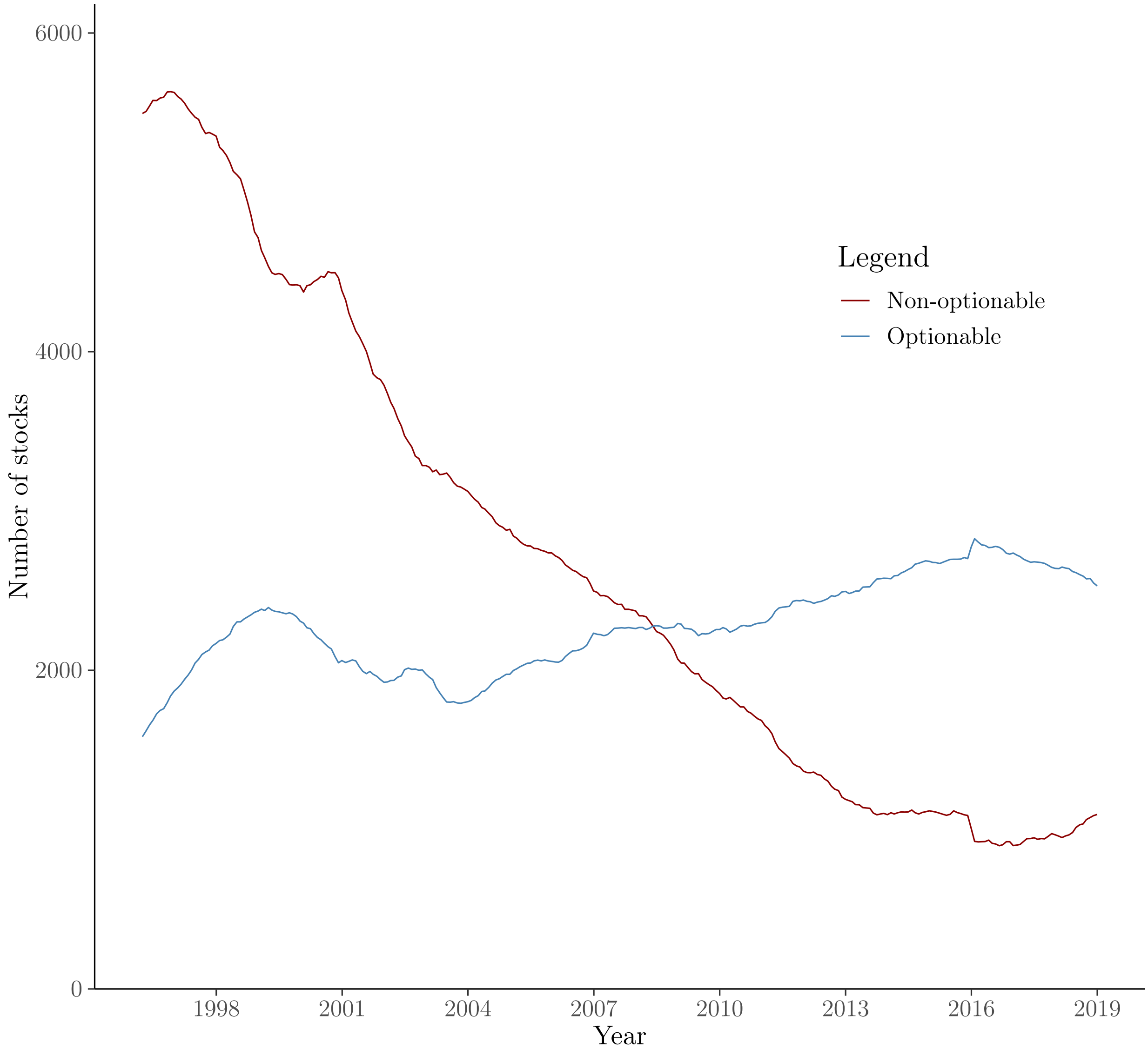
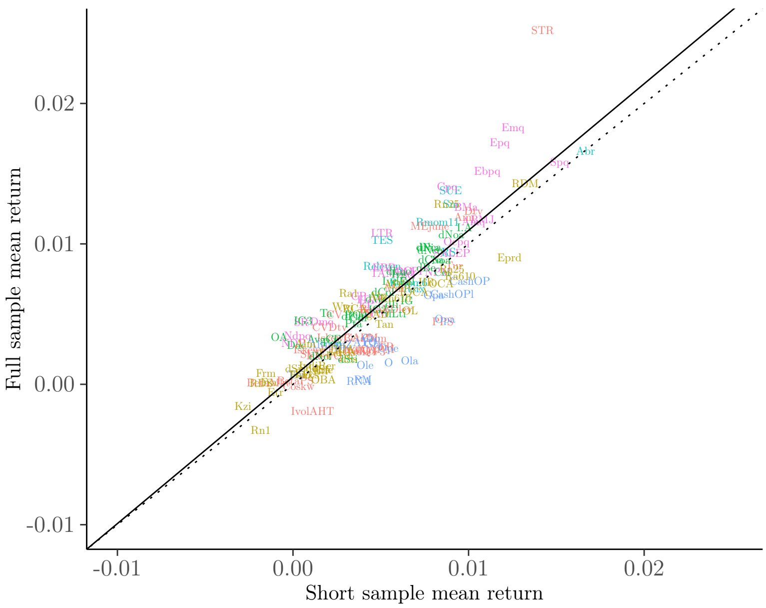


Figure A.2: Long Sample vs. Short Sample - Means and T-Values
We fit a linear model through anomaly returns and t-values calculated from Feb. 1996 to Dec. 2018 and anomaly returns and t-values calculated from Jan. 1967 to Dec. 2018. The t-values are adjusted for the differences in sample periods. The 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.

Panel A: Mean

$$\underset{(0.0003)}{\text{FS} = 0.0005} + \underset{(0.05)}{1.04} * \text{SS} + \varepsilon,\ R^2 = 75\%$$



Panel B: T-value

$$\underset{(0.13)}{\text{FS} = 0.34} + \underset{(0.05)}{1.14} * \text{SS} + \varepsilon,\ R^2 = 77\%$$

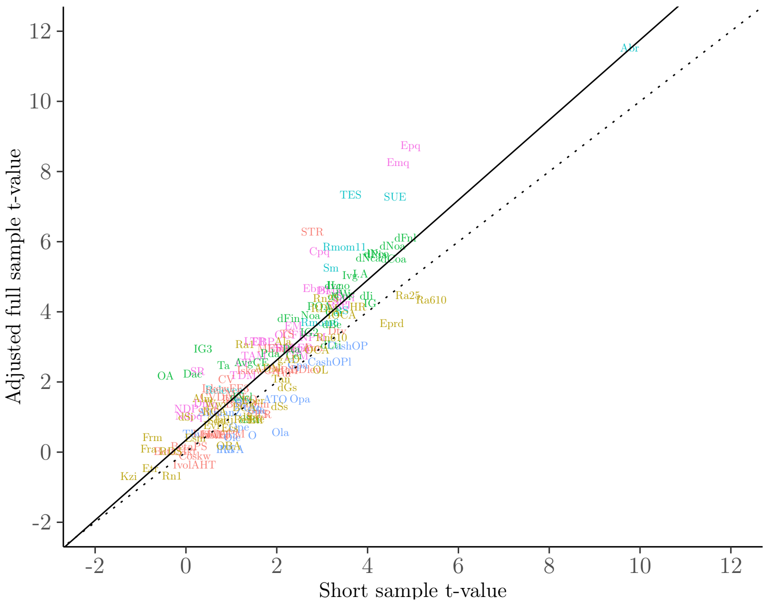


Figure A.3: Unadjusted Size and Liquidity Distributions
We show the empirical cumulative distribution function of the log of the one month lagged market equity and bid-ask spreads of optionable and non-optionable stocks for an exemplary month, here August 2012. A stock is considered optionable if it 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. The blue line shows the distribution for optionable stocks. The red line shows the distribution for non-optionable stocks.

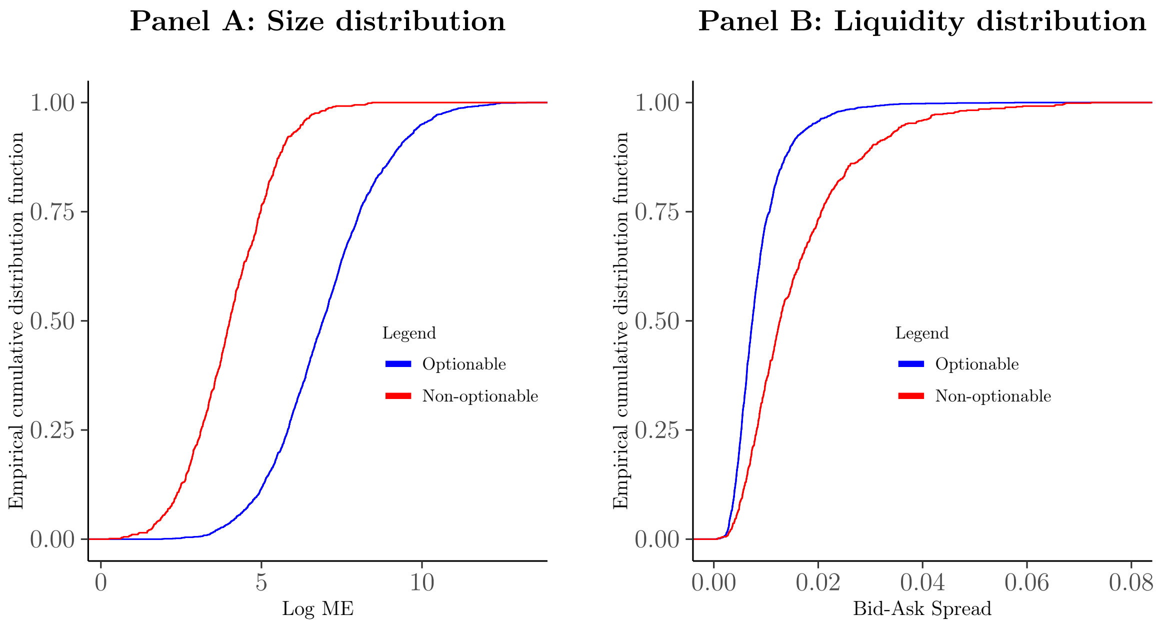
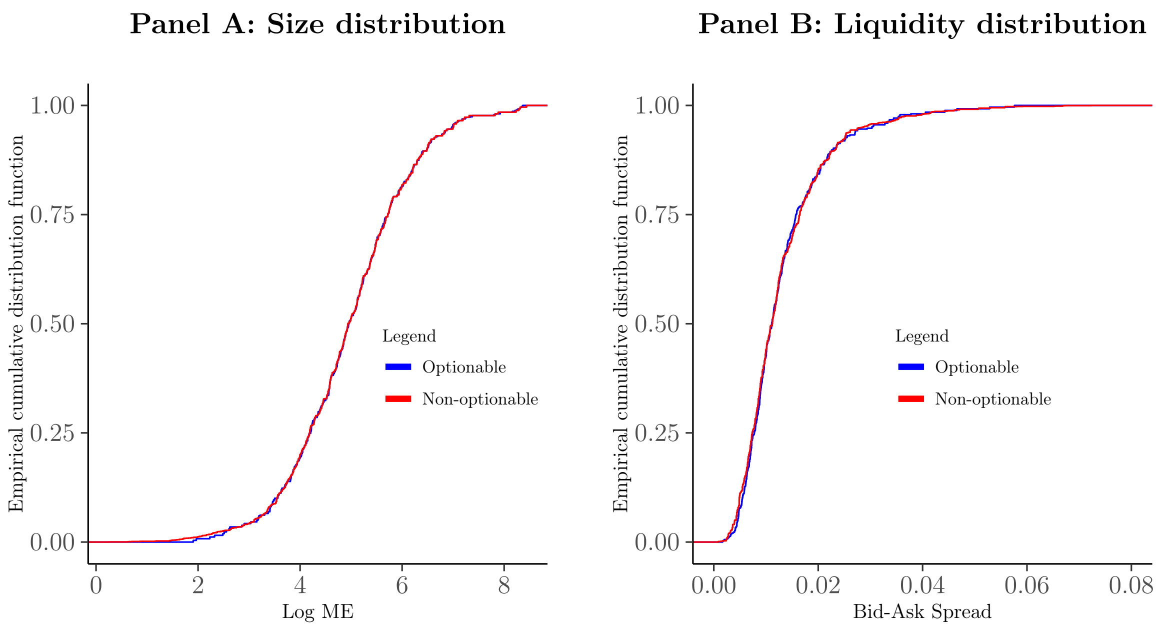


Figure A.4: Adjusted Size and Liquidity Distributions
For the same exemplary month, August 2012, we first adjust for differences in the one month lagged market equity and bid-ask spreads between optionable and non-optionable stocks. A stock is considered optionable if it has an entry in OptionMetrics at the portfolio formation date or up to 27 days before. When there is no OptionMetrics entry, the stock is considered non-optionable. We use a 100x10 adjustment with 5000 bootstrap iterations. We then show the empirical cumulative distribution functions of the log of the one month lagged market equity and bid-ask spreads. The blue line shows the distribution for optionable stocks. The red line shows the distribution for non-optionable stocks.



A.2 Tables

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

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

Table A.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. 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 brackets. 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 to December 2018.

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

Table A.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. We use 5000 bootstraps, resulting in 5000 aggregated anomaly portfolios. R is the average over 5000 time series mean returns. Similarly, α_{CAPM} is the average α from 5000 time series regressions of excess returns on the market factor. Average t-values are displayed in brackets. 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 to December 2018.

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

Table A.4: Returns on Anomaly Portfolios - Momentum
For each bootstrap iteration and each month, we average anomaly returns across our momentum category. 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 brackets. 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 A.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 to December 2018.

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

Table A.5: Returns on Anomaly Portfolios - Value
For each bootstrap iteration and each month, we average anomaly returns across our value category. 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 brackets. 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 A.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.

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

Table A.6: Returns on Anomaly Portfolios - Investment
For each bootstrap iteration and each month, we average anomaly returns across our investment category. 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 brackets. 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 A.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 to December 2018.

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

Table A.7: Returns on Anomaly Portfolios - Trading Frictions
For each bootstrap iteration and each month, we average anomaly returns across our trading friction category. 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 brackets. 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 A.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.

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

Table A.8: Returns on Anomaly Portfolios - Profitability
For each bootstrap iteration and each month, we average anomaly returns across our profitability category. 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 brackets. 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 A.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.

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

Table A.9: Returns on Anomaly Portfolios - Intangibles
For each bootstrap iteration and each month, we average anomaly returns across our intangibles category. 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 brackets. 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 A.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.

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

A.3 Further Analyses

This section of the appendix provides additional information and complementary results related to Chapter 2. Subsection A.3.1 presents additional figures, including a sanity check of the anomaly signal replication and a graphical representation of the bootstrap matching procedure. Subsection A.3.2 provides a more detailed description of the bootstrap matching procedure used to control for differences in size and liquidity.

A.3.1 Further Figures

Figure A.5: Replicating Anomalies - T-Value Comparison
To gauge our replication success of anomalies, we fit a linear model through our replicated t-statistics and the t-statistics documented by Hou et al. (2020). We use the set of equally-weighted anomalies with breakpoints calculated using the whole cross-section for the comparison. The y-axis depicts the t-values from our replication. The x-axis depicts the t-values documented by Hou et al. (2020). 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. We sort out financial firms and firms with negative book equity. The sample period is January 1967 to December 2016, if not stated otherwise by Hou et al. (2020).

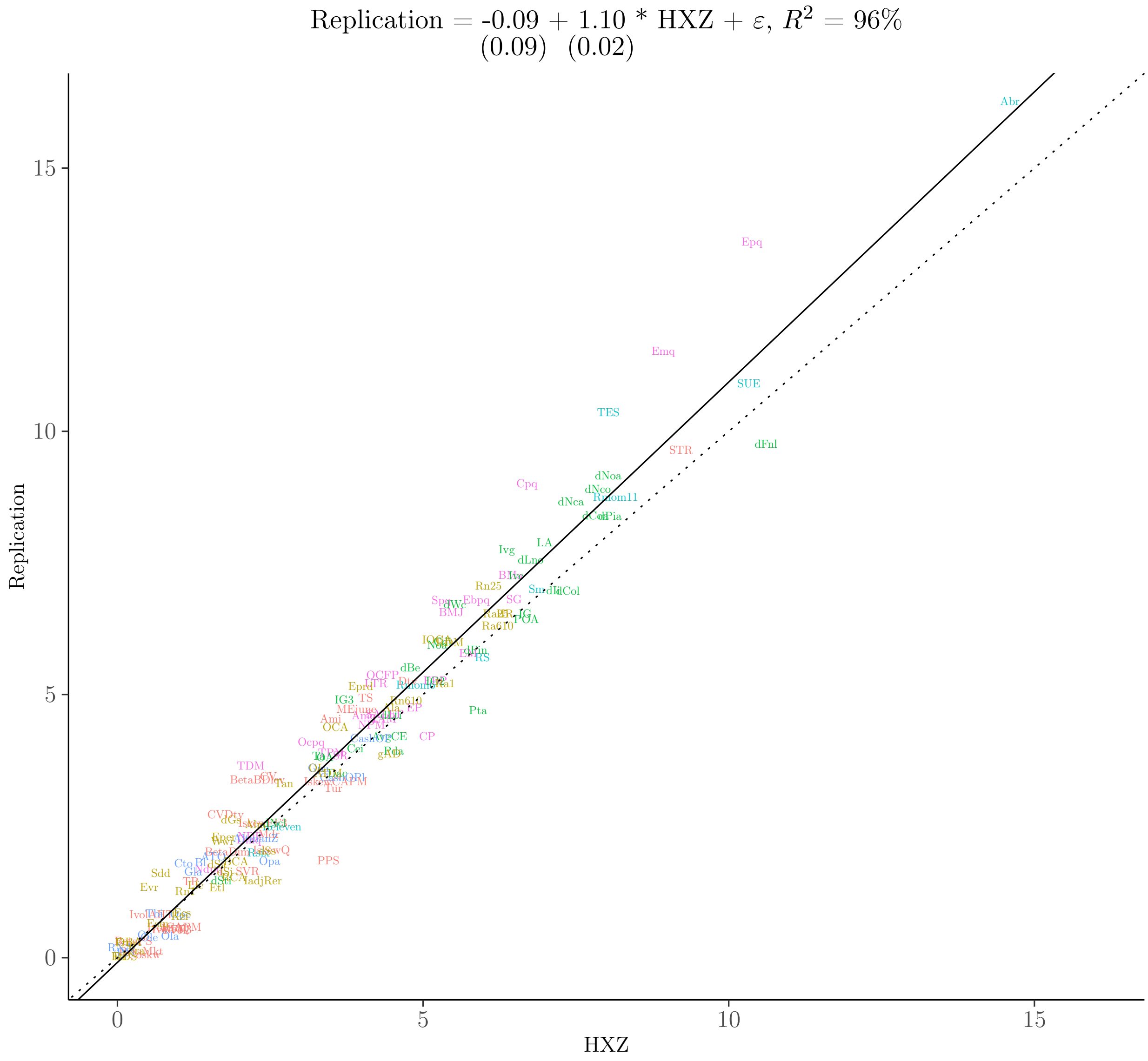
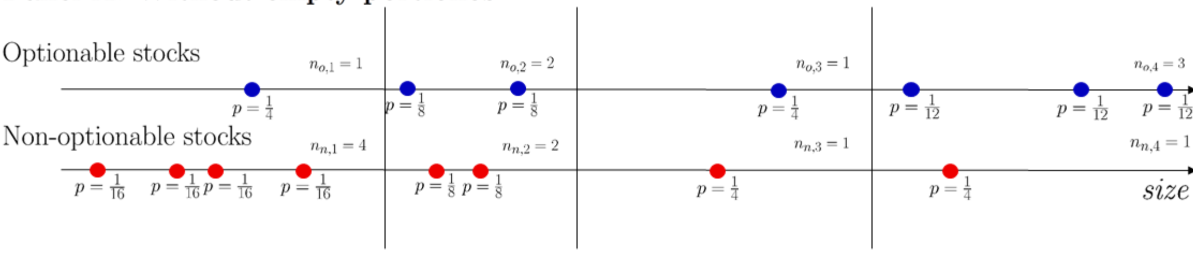


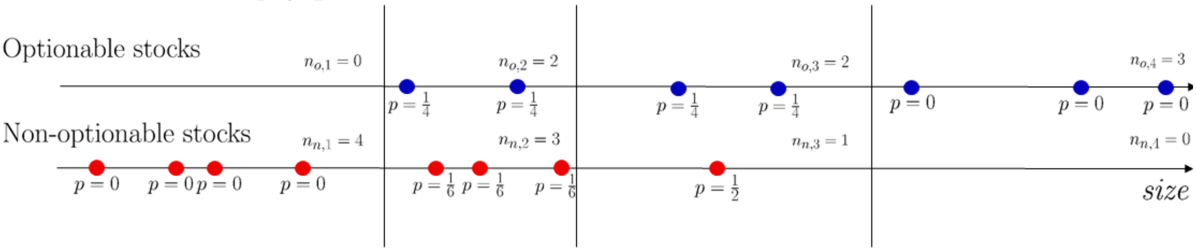
Figure A.6: A Graphic Illustration of the Bootstrap Approach

The two graphs exemplify the bootstrap approach, with which we control for size and liquidity. The horizontal lines represent the sizes of the firms. The vertical lines represent portfolio breakpoints. In this example, we sort stocks into four portfolios. The blue dots represent optionable and the red dots non-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. Panel A shows a situation in which there is a positive number of optionable and also non-optionable stocks on all four portfolios. Panel B shows a situation in which some portfolios are empty.

Panel A: Without empty portfolios



Panel B: With empty portfolios



A.3.2 Bootstrap Matching Procedure

This section provides a detailed explanation of the empirical bootstrap procedure used to compare anomaly returns between stocks with and without listed options, while controlling for differences in size and liquidity.

A.3.2.1 Bootstrap Procedure: One-Dimensional Matching

The bootstrap approach starts with a portfolio sort, as illustrated in the top panel of Figure A.6. We first explain the approach using a single characteristic—size—and then extend it to the case of two characteristics, namely size and liquidity. In a given month, suppose we observe N_o optionable stocks and N_n non-optionable stocks (in the example, $N_o = 7$ and $N_n = 8$). For both groups, we sort stocks into K bins based on size (in the example, $K = 4$), using the same breakpoints $B_1, \ldots, B_{K-1}$. The selection of breakpoints is discussed later. Let $n_{o,k}$ and $n_{n,k}$ denote the number of optionable and non-optionable stocks in bin k, respectively, for $k = 1, \ldots, K$. Provided that no bin is empty, i.e., $n_{o,k} > 0$ and $n_{n,k} > 0$, we assign sampling probabilities such that stocks in each bin have equal total weight:

$$\begin{aligned} \text{Optionable:} \quad & \frac{1}{K \cdot n_{o,k}} \quad \text{for stocks in bin } k \\ \text{Non-optionable:} \quad & \frac{1}{K \cdot n_{n,k}} \quad \text{for stocks in bin } k \end{aligned}$$

This weighting ensures that the probability of drawing a stock from any bin k is always equal to $\frac{1}{K}$. As a result, if K is sufficiently large, this procedure corrects for over-representation of certain size segments (e.g., small firms among non-optionable stocks) and generates bootstrap samples with similar size distributions across the two groups.

To understand the difference compared to a standard bootstrap, consider the group of non-optionable stocks in our example. A standard bootstrap would assign each stock an equal probability of $\frac{1}{N_n} = \frac{1}{8}$, effectively treating the sample as if there were two stocks in each of the four bins. In reality, however, the distribution is uneven: there are many non-optionable stocks in the lower-size bins (e.g., $n_{n,1} = 4$) and few in the higher-size bins (e.g., $n_{n,4} = 1$). As a consequence, our bootstrap design assigns a lower probability of $\frac{1}{Kn_{n,1}} = \frac{1}{16}$ to small non-optionable stocks and a higher probability of $\frac{1}{Kn_{n,4}} = \frac{1}{4}$ to large non-optionable stocks.

Handling Empty Bins. If a bin is empty for either group, we exclude it from resampling and renormalize the weights based on the number of overlapping bins $K^* < K$. In practice, using common breakpoints for two different sets of stocks often results in empty bins, especially when the distributions of the characteristic used for sorting differ substantially between the groups. This situation is illustrated in the lower panel of Figure A.6. If, for a given bin, there are no stocks from one of the two groups, we thus also assign zero probability to all stocks in that bin from the other group. Intuitively, we must exclude stocks that do not have a counterpart in the other group, i.e., stocks that are not comparable in terms of size. To ensure that the sampling probabilities again add up to one, we replace $K = 4$ with the number of bins $K^* = 2$ that contain at least one stock from both groups when calculating probabilities.

Constructing Breakpoints. Our choice of breakpoints is guided by the goal of minimizing the number of empty bins and, consequently, reducing the number of stocks excluded from the sample. At the same time, we aim to avoid very large bins at the extremes, as substantial within-portfolio variation in size would undermine our objective of constructing samples with matching distributions.

Breakpoints are derived as a convex combination of group-specific quantiles. More formally, in each month, let $B_{o,k}$ and $B_{n,k}$ be the k^{th} quantile for optionable and non-optionable stocks. The final breakpoint is:

$$B_k = wB_{o,k} + (1 - w)B_{n,k}$$

We set the weight w to minimize the number of empty bins and maximize joint coverage.

A.3.2.2 Extension to Two-Dimensional Matching

To jointly control for size and liquidity,[12] we begin by determining 99 size breakpoints following the procedure described above. Within each size portfolio, we then select nine liquidity breakpoints, again aiming to minimize the number of stocks that need to be dropped. This yields a $100 \times 10 = 1{,}000$ grid of two-way bins. Each stock falls into one combined bin defined by its size and liquidity ranking. Sampling weights are then assigned analogously to the one-dimensional case, ensuring uniform representation across the full grid.

This fine partitioning leads to a time-series dropout rate of approximately 59%, on average. The number of bins reflects a trade-off between accuracy and coverage. Using 100×10 bins allows us to closely match the size and liquidity distributions between optionable and non-optionable stocks. This design is intentionally conservative, prioritizing precision over the number of stocks retained. Increasing the number of bins beyond 100×10 does not materially improve the match in distributions. Reducing the number, on the other hand, increases the number of stocks with non-zero sampling probabilities, but weakens the control for size and liquidity. Our

[12] The sorting approach can be generalized to more than two characteristics by constructing a $K_1 \times \cdots \times K_d$ grid for d characteristics.

main findings remain qualitatively unchanged when using fewer bins, though the effects tend to be less pronounced.

A.3.2.3 Implementation

In each month, we draw 5000 bootstrap samples using the constructed sampling weights and compute the average anomaly return for each group. We report the average return differential across these resampled distributions, along with bootstrapped t-statistics. As a benchmark, we also implement a uniform resampling scheme (i.e., with weights $1/N_o$ and $1/N_n$), which recovers the raw sample means.

A.3.2.4 Comparison to Other Matching Methods

An alternative approach to control for characteristics such as size and liquidity is 1:1 matching, which can be viewed as an extreme case of our method where the number of portfolios is so large that each contains exactly one stock. This approach offers the advantage of directly pairing each stock with an exact counterpart, maximizing comparability between groups. However, in practice, it often suffers from severe limitations: many portfolios remain empty due to distributional differences, resulting in a significant loss of observations and reduced statistical power. In the context of optionability, Abhyankar et al. (2024), Bernile et al. (2025), and Cao et al. (2024) apply more flexible versions of 1:1 matching. Rather than requiring exact matches, Cao et al. (2024) sort into $100 \times 3 \times 3$ portfolios based on size, past return, and return volatility, and match stocks within the same portfolio.

Abhyankar et al. (2024) match each optionable stock with a non-optionable stock that is larger and more liquid. While pragmatic, this approach risks producing groups that remain incomparable in terms of the control variable, yielding opposite effects after matching (see Panel B of Table 2 in their paper). Additionally, unlike our method, their approach restricts each stock-month observation to be used only once, thereby reducing the overall sample size. For comparison, when analyzing cross-sections of stocks with non-missing momentum characteristics, Abhyankar et al. (2024) use an average of 454 optionable and 454 non-optionable stocks, whereas our method draws from an average of 538 optionable and 894 non-optionable stocks.

Bernile et al. (2025) estimate a propensity score by fitting a logit model of an optionability dummy on covariates such as size and liquidity. Each optionable stock is then matched to a non-optionable stock with a similar propensity score. Their model assumes a linear relation between the (transformed) propensity and the covariates. However, the validity of this linearity assumption is difficult to verify. For example, the right graph of Figure A.3 suggests that there are nonlinearities in the relation between optionability and liquidity. While the approach can be extended to more flexible, nonlinear models, it still requires assumptions about the functional form of the propensity score. In contrast, our method is entirely model-free and avoids imposing any such structure.

All 1:1 matching procedures are potentially susceptible to selection biases. From a potentially large pool of suitable matches, these methods select a single observation for each treated stock, which may not be representative. A key advantage of our bootstrap approach is that it treats all eligible candidates equally—each one can, and eventually will, be drawn during the resampling process. As a result, the reported statistics are more likely to reflect the properties of the full (controlled) sample rather than those of a specific, potentially biased subset of matched stocks.

Appendix B

How Option Traders Take Sides on Return Predictability

This appendix presents the main figures and tables associated with Chapter 3. Section B.1 contains the figures, while Section B.2 reports the corresponding tables. Additionally, Section B.3 explains the algorithm used to create anomaly clusters.

B.1 Figures

Figure B.1: Long-short Conversion Returns Across Economic Categories
In each month, we aggregate equally-weighted long-short conversion returns of anomalies across each economic category. We plot the average long-short conversion return of each economic category on the y-axis and the name of the economic category on the x-axis. The error bars in red represent a 99% confidence interval for the average long-short conversion returns. Standard errors are adjusted according to Newey and West (1987). The sample covers the period from January 1996 to June 2021.

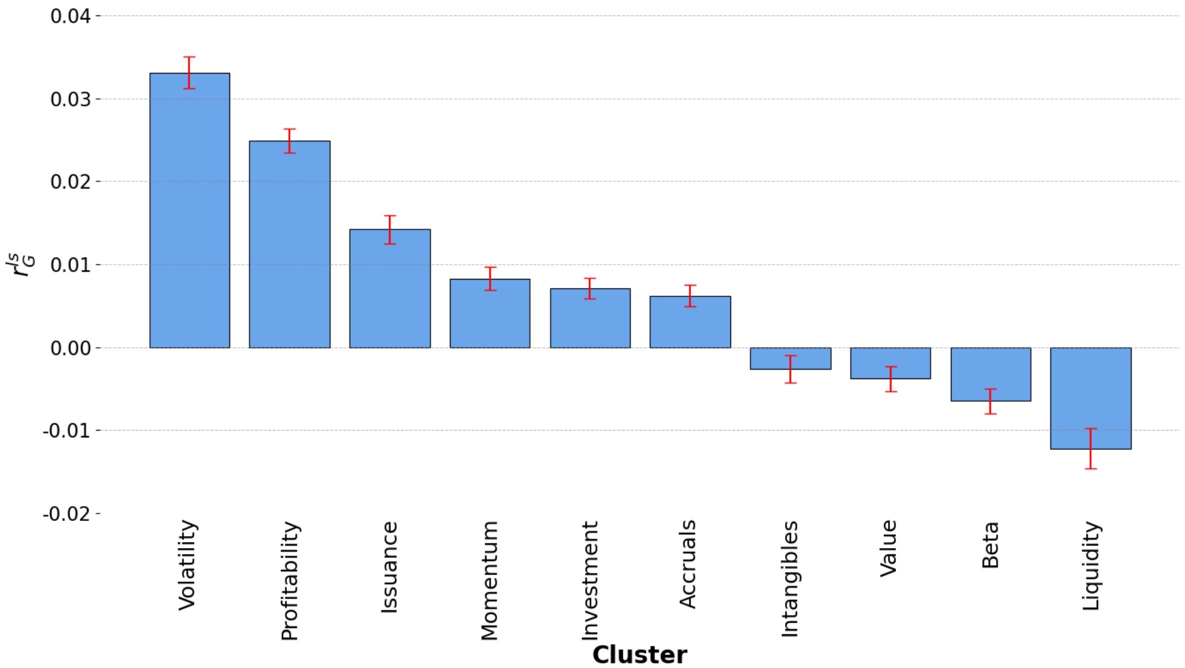


Figure B.2: Long-Short Conversion Returns and Trading Costs Across Economic Categories

In each month, we aggregate equally-weighted long-short conversion returns of anomalies across each economic category. We plot the average long-short conversion return of each economic category on the y-axis and the name of the economic category on the x-axis. The bars in red represent the trading costs centered around the mean long-short conversion return for the respective strategy. We multiply option quoted half spreads from OptionMetrics with a multiplier derived from Muravyev and Pearson (2020) to calculate effective half spreads. The cost categories $Costs_{ES}$, $Costs_{ADJES}$, $Costs_{ALGOES}$ show costs when we use multipliers based on the different kinds of spreads that Muravyev and Pearson (2020) provide. The sample covers the period from January 1996 to June 2021.

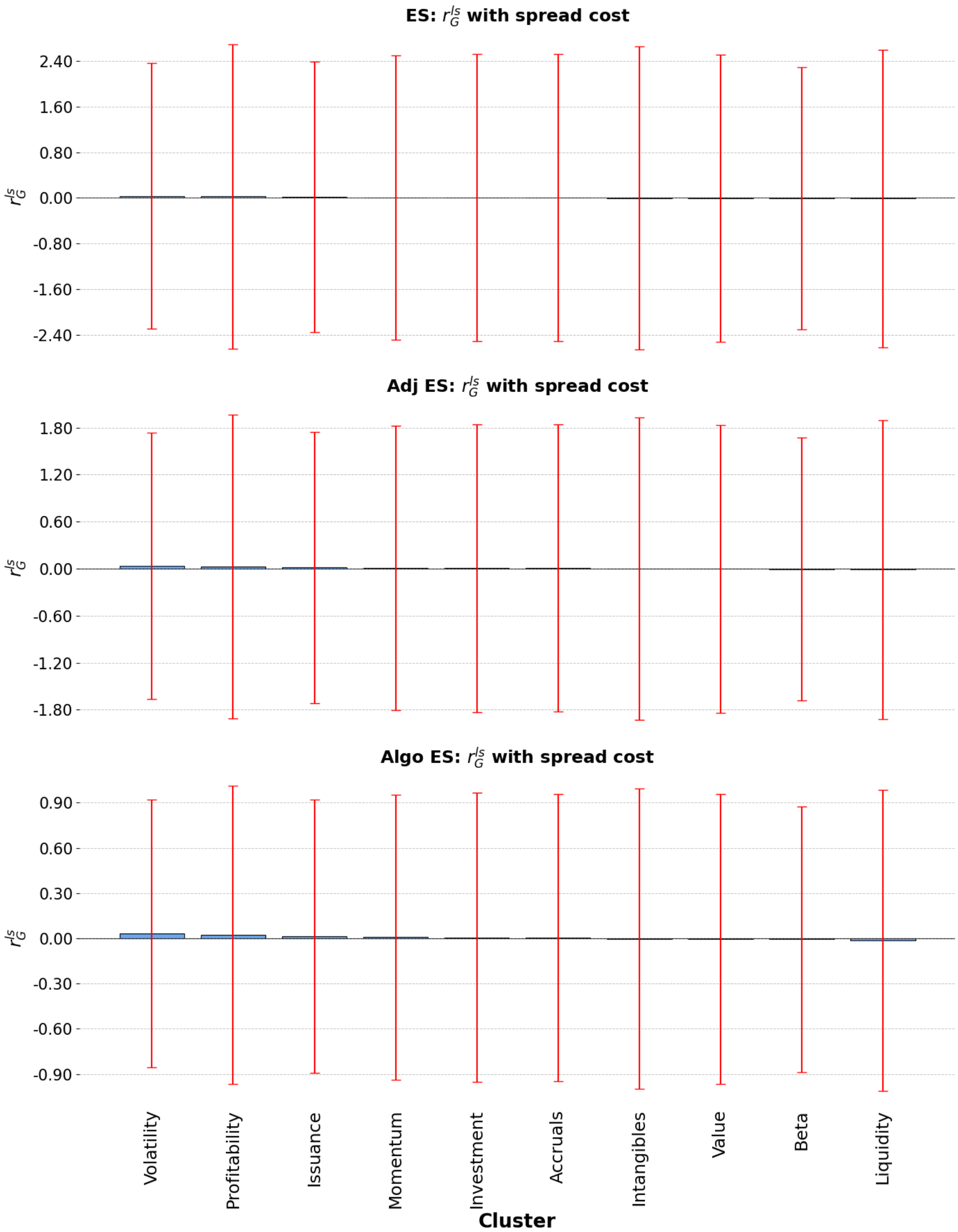
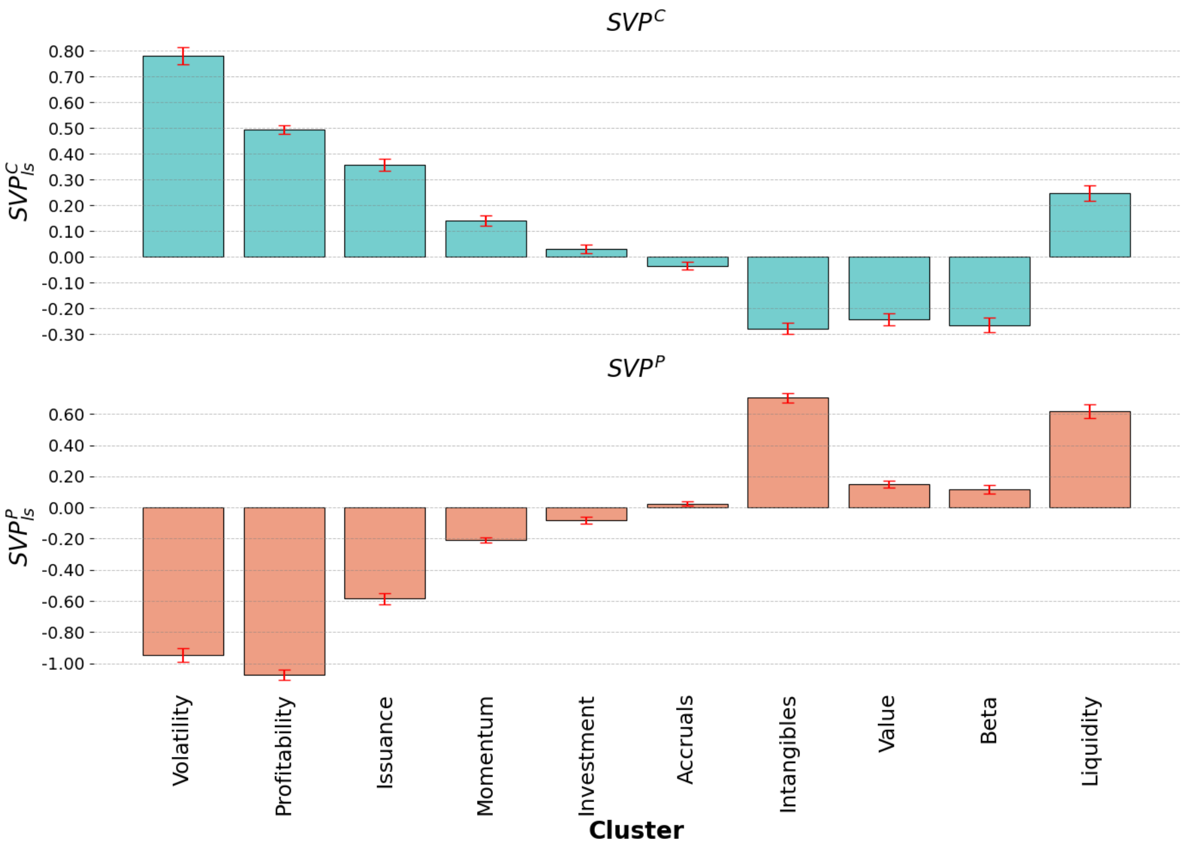


Figure B.3: Semivariance Premia Across Economic Categories
In each month, we aggregate equally-weighted long-short semivariance premia of anomalies across each economic category. We plot the average long-short semivariance premia of each economic category on the y-axis and the name of the economic category on the x-axis. The error bars in red represent a 99% confidence interval for the average long-short conversion returns. Standard errors are adjusted according to Newey and West (1987). Because we use security price data from OptionMetrics to compute semivariance premia, the sample covers the period from February 1996 to June 2021.



B.2 Tables

Table B.1: Descriptive Statistics of Conversion Returns and Semivariance Premia
This table shows descriptive statistics of of conversion/excess conversion returns and upper/lower semivariance premia in percentage. For each variable, we show the total observations, full-sample mean pooled across assets and time, standard deviation, the 25%, 50% (median), 75% quantiles and skewness and kurtosis.

	N	mean	std	25%	50%	75%	skewness	kurtosis
Panel A: Conversion returns								
r_G	9,075,240	0.11	0.40	-0.09	0.09	0.30	0.01	2.16
r_G^e	9,075,240	-0.07	0.40	-0.24	-0.05	0.10	-0.16	2.43
Panel B: Semivariance premia								
SVP^+	14,505,391	-0.14	0.30	-0.26	-0.06	0.04	-1.31	1.72
SVP^-	14,505,391	0.40	0.53	0.02	0.24	0.65	1.22	0.88
VP	14,505,391	0.22	0.58	-0.14	0.10	0.51	0.79	0.46

Table B.2: Long-Short Conversion Returns and Semivariance Premia Averaged Across all Anomaly Signals

On each day, we average equally-weighted long-short conversion returns and semivariance premia across all three groups of signals: 243 total signals, 155 predictors and 86 placebos. t-statistics are shown in parantheses. Standard errors are adjusted according to Newey and West (1987). Excess conversion returns and semivariance premia are displayed in percentages. The sample covers the period from January 1996 to June 2021 for long-short conversion returns and February 1996 to June 2021 for long-short semivariance premia.

	Portfolio 1	Portfolio 10	10-1	t(10-1)
Panel A: All 243 anomalies				
r_S	0.0411	0.0564	0.0153	(5.13)
r_G	0.1000	0.1067	0.0067	(9.03)
SVP^+	-0.2228	-0.2104	0.0124	(8.17)
SVP^-	0.5305	0.5123	-0.0183	(-4.72)
Panel B: 155 predictors				
r_S	0.0405	0.0574	0.0170	(4.64)
r_G	0.0997	0.1070	0.0072	(7.67)
SVP^+	-0.2380	-0.2010	0.0370	(6.18)
SVP^-	0.5428	0.4800	-0.0628	(-2.38)
Panel C: 86 significant signals on optionable sample				
r_S	0.0323	0.0623	0.0300	(5.80)
r_G	0.0966	0.1082	0.0116	(10.92)
SVP^+	-0.2509	-0.1951	0.0558	(10.09)
SVP^-	0.6360	0.4434	-0.1926	(-11.61)

Table B.3: Long-Short Conversion Return Predictability
On each day, we average equally-weighted long-short conversion returns of anomaly groups which generate positive long-short conversion returns: volatility, profitability, momentum. We show the results for monthly predictive regressions of the aggregated long-short conversion return on a set of predictors indicated by the rows. Columns (1) to (5) contain the results for univariate regressions, while column (6) contains the results for a multivariate regression including all the predictors. We standardize the independent variables and multiply the dependent variable by 1000 for the readability. Each row before last row reports the estimated coefficient and t-statistics are shown in parentheses. Standard errors are adjusted according to Newey and West (1987).The last row depicts the adjusted R^2. *, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively. Because shorting fee data is only available from July 2006, the sample ranges from August 2006 to June 2021.

	Dependent variable: Average (all anomalies) long-short $r_{G,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.26***	1.26***	1.26***	1.26***	1.26***	1.26***
	(21.11)	(19.38)	(18.88)	(18.02)	(18.29)	(10.97)
SF_{t-1}	-0.06					0.05
	(-1.04)					(1.14)
ICR_{t-1}		-0.23***				-0.12***
		(-3.87)				(-3.96)
TED_{t-1}			-0.01			0.26***
			(-1.04)			(3.72)
Ami_{t-1}				0.03		-0.05*
				(0.60)		(-1.89)
Oba_{t-1}					-0.01	-0.03
					(-0.50)	(-0.83)
$retG_{t-1}$						0.77***
						(13.04)
$Adj.R^2$	0.04	0.02	0.06	0.01	0.01	0.46

Table B.4: Overview over Anomaly Signals
This table describes the anomaly signals from Chen and Zimmermann (2022) that we use in our analyses. We limit ourselves to continuous signals which are not constructed using options data and which have enough data coverage to calculate long-short returns. we further cluster them into 10 groups based on our clustering method.

Acronym	Description	Signal Type	Author
	Accruals		
AbnormalAccruals	Abnormal Accruals	Predictor	Xie 2001
AbnormalAccrualsPercent	Percent Abnormal Accruals	Placebo	Hafzalla, Lundholm, Van Winkle 2011
Accruals	Accruals	Predictor	Sloan 1996
AssetGrowth	Asset growth	Predictor	Cooper, Gulen and Schill 2008
AssetGrowth_q	Asset growth quarterly	Placebo	Cooper, Gulen and Schill 2008
ChAssetTurnover	Change in Asset Turnover	Predictor	Soliman 2008
ChEQ	Growth in book equity	Predictor	Lockwood and Prombutr 2010
ChNCOA	Change in Noncurrent Operating Assets	Placebo	Soliman 2008
ChNCOL	Change in Noncurrent Operating Liab	Placebo	Soliman 2008
ChNNCOA	Change in Net Noncurrent Op Assets	Predictor	Soliman 2008
ChNWC	Change in Net Working Capital	Predictor	Soliman 2008
ChPM	Change in Profit Margin	Placebo	Soliman 2008
ChangeInRecommendation	Change in recommendation	Predictor	Jegadeesh et al. 2004
Coskewness	Coskewness	Predictor	Harvey and Siddique 2000
DelCOA	Change in current operating assets	Predictor	Richardson et al. 2005
DelCOL	Change in current operating liabilities	Predictor	Richardson et al. 2005
DelEqu	Change in equity to assets	Predictor	Richardson et al. 2005
GrAdExp	Growth in advertising expenses	Predictor	Lou 2014
GrSaleToGrOverhead	Sales growth over overhead growth	Predictor	Abarbanell and Bushee 1998
GrSaleToGrReceivables	Change in sales vs change in receiv	Placebo	Abarbanell and Bushee 1998
IntMom	Intermediate Momentum	Predictor	Novy-Marx 2012
LaborforceEfficiency	Laborforce efficiency	Placebo	Abarbanell and Bushee 1998
MomSeasonShort	Return seasonality last year	Predictor	Heston and Sadka 2008
PS	Piotroski F-score	Predictor	Piotroski 2000
PctAcc	Percent Operating Accruals	Predictor	Hafzalla, Lundholm, Van Winkle 2011
PctTotAcc	Percent Total Accruals	Predictor	Hafzalla, Lundholm, Van Winkle 2011
TotalAccruals	Total accruals	Predictor	Richardson et al. 2005
dNoa	change in net operating assets	Predictor	Hirshleifer, Hou, Teoh, Zhang 2004
hire	Employment growth	Predictor	Bazdresch, Belo and Lin 2014
saleinv	Sales to inventory	Placebo	Ou and Penman 1989
	Beta		
AdExp	Advertising Expense	Predictor	Chan, Lakonishok and Sougiannis 2001
AssetTurnover	Asset Turnover	Placebo	Soliman 2008
AssetTurnover_q	Asset Turnover	Placebo	Soliman 2008
Beta	CAPM beta	Predictor	Fama and MacBeth 1973
BetaFP	Frazzini-Pedersen Beta	Predictor	Frazzini and Pedersen 2014
BetaLiquidityPS	Pastor-Stambaugh liquidity beta	Predictor	Pastor and Stambaugh 2003
BetaTailRisk	Tail risk beta	Predictor	Kelly and Jiang 2014
BrandCapital	Brand capital to assets	Placebo	Belo, Lin and Vitorino 2014
CapTurnover	Capital turnover	Placebo	Haugen and Baker 1996
CapTurnover_q	Capital turnover (quarterly)	Placebo	Haugen and Baker 1996
DelLTI	Change in long-term investment	Predictor	Richardson et al. 2005
DelSTI	Change in short-term investment	Placebo	Richardson et al. 2005
DownsideBeta	Downside beta	Placebo	Ang, Chen and Xing 2006
ForecastDispersionLT	Long-term forecast dispersion	Placebo	Anderson, Ghysels, and Juergens 2005
GrLTNOA	Growth in long term operating assets	Predictor	Fairfield, Whisenant and Yohn 2003
OPLeverage	Operating leverage	Predictor	Novy-Marx 2011
OPLeverage_q	Operating leverage (qtrly)	Placebo	Novy-Marx 2011
OrgCap	Organizational capital	Predictor	Eisfeldt and Papanikolaou 2013

Continued on next page

Table B.4 – continued from previous page

Acronym	Description	Signal Type	Author
OrgCapNoAdj	Org cap w/o industry adjustment	Placebo	Eisfeldt and Papanikolaou 2013
betaRR	Return-market return illiquidity beta	Placebo	Acharya and Pedersen 2005
	Intangibles		
AssetLiquidityBook	Asset liquidity over book assets	Placebo	Ortiz-Molina and Phillips 2014
AssetLiquidityBookQuart	Asset liquidity over book (qtrly)	Placebo	Ortiz-Molina and Phillips 2014
BPEBM	Leverage component of BM	Predictor	Penman, Richardson and Tuna 2007
BookLeverage	Book leverage (annual)	Predictor	Fama and French 1992
BookLeverageQuarterly	Book leverage (quarterly)	Placebo	Fama and French 1992
Cash	Cash to assets	Predictor	Palazzo 2012
EBM	Enterprise component of BM	Predictor	Penman, Richardson and Tuna 2007
EBM_q	Enterprise component of BM	Placebo	Penman, Richardson and Tuna 2007
Herf	Industry concentration (sales)	Predictor	Hou and Robinson 2006
HerfAsset	Industry concentration (assets)	Predictor	Hou and Robinson 2006
HerfBE	Industry concentration (equity)	Predictor	Hou and Robinson 2006
KZ	Kaplan Zingales index	Placebo	Lamont, Polk and Saa-Requejo 2001
KZ_q	Kaplan Zingales index quarterly	Placebo	Lamont, Polk and Saa-Requejo 2001
NOA	Net Operating Assets	Predictor	Hirshleifer et al. 2004
NetDebtPrice	Net debt to price	Predictor	Penman, Richardson and Tuna 2007
NetDebtPrice_q	Net debt to price	Placebo	Penman, Richardson and Tuna 2007
OrderBacklog	Order backlog	Predictor	Rajgopal, Shevlin, Venkatachalam 2003
RD	R&D over market cap	Predictor	Chan, Lakonishok and Sougiannis 2001
RD_q	R&D over market cap quarterly	Placebo	Chan, Lakonishok and Sougiannis 2001
depr	Depreciation to PPE	Placebo	Holthausen and Larcker 1992
pchdepr	Change in depreciation to PPE	Placebo	Holthausen and Larcker 1992
rd_sale	R&D to sales	Placebo	Chan, Lakonishok and Sougiannis 2001
rd_sale_q	R&D to sales	Placebo	Chan, Lakonishok and Sougiannis 2001
tang	Tangibility	Predictor	Hahn and Lee 2009
tang_q	Tangibility quarterly	Placebo	Hahn and Lee 2009
	Investment		
AccrualQuality	Accrual Quality	Placebo	Francis, LaFond, Olsson, Schipper 2005
BetaBDLeverage	Broker-Dealer Leverage Beta	Placebo	Adrian, Etula and Muir 2014
CF	Cash flow to market	Predictor	Lakonishok, Shleifer, Vishny 1994
CFq	Cash flow to market quarterly	Placebo	Lakonishok, Shleifer, Vishny 1994
ChInv	Inventory Growth	Predictor	Thomas and Zhang 2002
ChInvIA	Change in capital inv (ind adj)	Predictor	Abarbanell and Bushee 1998
DelFINL	Change in financial liabilities	Predictor	Richardson et al. 2005
DelNetFin	Change in net financial assets	Predictor	Richardson et al. 2005
DelayAcct	Accounting component of price delay	Placebo	Callen, Khan and Lu 2013
EPq	Earnings-to-Price Ratio	Placebo	Basu 1977
EntMult	Enterprise Multiple	Predictor	Loughran and Wellman 2011
EntMult_q	Enterprise Multiple quarterly	Placebo	Loughran and Wellman 2011
ExclExp	Excluded Expenses	Predictor	Doyle, Lundholm and Soliman 2003
GrGMToGrSales	Gross margin growth to sales growth	Placebo	Abarbanell and Bushee 1998
GrSaleToGrInv	Sales growth over inventory growth	Predictor	Abarbanell and Bushee 1998
InvGrowth	Inventory Growth	Predictor	Belo and Lin 2012
InvestPPEInv	change in ppe and inv/assets	Predictor	Lyandres, Sun and Zhang 2008
Investment	Investment to revenue	Predictor	Titman, Wei and Xie 2004
MomOffSeason16YrPlus	Off season reversal years 16 to 20	Predictor	Heston and Sadka 2008
NetDebtFinance	Net debt financing	Predictor	Bradshaw, Richardson, Sloan 2006
cfp	Operating Cash flows to price	Predictor	Desai, Rajgopal, Venkatachalam 2004
cfpq	Operating Cash flows to price quarterly	Placebo	Desai, Rajgopal, Venkatachalam 2004
grcapx	Change in capex (two years)	Predictor	Anderson and Garcia-Feijoo 2006
grcapx1y	Investment growth (1 year)	Placebo	Anderson and Garcia-Feijoo 2006
grcapx3y	Change in capex (three years)	Predictor	Anderson and Garcia-Feijoo 2006
pchgm_pchsale	Change in gross margin vs sales	Placebo	Abarbanell and Bushee 1998
pchsaleinv	Change in sales to inventory	Placebo	Ou and Penman 1989

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Table B.4 – continued from previous page

Acronym	Description	Signal Type	Author
		Issuance	
AOP	Analyst Optimism	Predictor	Frankel and Lee 1998
AnalystRevision	EPS forecast revision	Predictor	Hawkins, Chamberlin, Daniel 1984
CompositeDebtIssuance	Composite debt issuance	Predictor	Lyandres, Sun and Zhang 2008
EP	Earnings-to-Price Ratio	Predictor	Basu 1977
EquityDuration	Equity Duration	Predictor	Dechow, Sloan and Soliman 2004
IntrinsicValue	Intrinsic or historical value	Placebo	Frankel and Lee 1998
MomOffSeason06YrPlus	Off season reversal years 6 to 10	Predictor	Heston and Sadka 2008
NetEquityFinance	Net equity financing	Predictor	Bradshaw, Richardson, Sloan 2006
NetPayoutYield	Net Payout Yield	Predictor	Boudoukh et al. 2007
OrderBacklogChg	Change in order backlog	Predictor	Baik and Ahn 2007
PM	Profit Margin	Placebo	Soliman 2008
PayoutYield_q	Payout Yield quarterly	Placebo	Boudoukh et al. 2007
PredictedFE	Predicted Analyst forecast error	Predictor	Frankel and Lee 1998
RoE	net income / book equity	Predictor	Haugen and Baker 1996
ShareIss1Y	Share issuance (1 year)	Predictor	Pontiff and Woodgate 2008
ShareIss5Y	Share issuance (5 year)	Predictor	Daniel and Titman 2006
XFIN	Net external financing	Predictor	Bradshaw, Richardson, Sloan 2006
		Liquidity	
Activism1	Takeover vulnerability	Predictor	Cremers and Nair 2005
BidAskSpread	Bid-ask spread	Predictor	Amihud and Mendelson 1986
DelayNonAcct	Non-accounting component of price delay	Placebo	Callen, Khan and Lu 2013
DolVol	Past trading volume	Predictor	Brennan, Chordia, Subra 1998
EarnSupBig	Earnings surprise of big firms	Predictor	Hou 2007
FirmAge	Firm age based on CRSP	Predictor	Barry and Brown 1984
Illiquidity	Amihud's illiquidity	Predictor	Amihud 2002
IndMom	Industry Momentum	Predictor	Grinblatt and Moskowitz 1999
PriceDelayRsq	Price delay r square	Predictor	Hou and Moskowitz 2005
PriceDelaySlope	Price delay coeff	Predictor	Hou and Moskowitz 2005
ShortInterest	Short Interest	Predictor	Dechow et al. 2001
VolMkt	Volume to market equity	Predictor	Haugen and Baker 1996
VolSD	Volume Variance	Predictor	Chordia, Subra, Anshuman 2001
VolumeTrend	Volume Trend	Predictor	Haugen and Baker 1996
WW	Whited-Wu index	Placebo	Whited and Wu 2006
WW_Q	Whited-Wu index	Placebo	Whited and Wu 2006
betaCC	Illiquidity-illiquidity beta (beta2i)	Placebo	Acharya and Pedersen 2005
betaNet	Net liquidity beta (betanet,p)	Placebo	Acharya and Pedersen 2005
secured	Secured debt	Placebo	Valta 2016
zerotrade12M	Days with zero trades	Predictor	Liu 2006
zerotrade1M	Days with zero trades	Predictor	Liu 2006
zerotrade6M	Days with zero trades	Predictor	Liu 2006
		Momentum	
AnnouncementReturn	Earnings announcement return	Predictor	Chan, Jegadeesh and Lakonishok 1996
ChTax	Change in Taxes	Predictor	Thomas and Zhang 2011
ChangeRoA	Change in Return on assets	Placebo	Balakrishnan, Bartov and Faurel 2010
ChangeRoE	Change in Return on equity	Placebo	Balakrishnan, Bartov and Faurel 2010
CoskewACX	Coskewness using daily returns	Predictor	Ang, Chen and Xing 2006
CustomerMomentum	Customer momentum	Predictor	Cohen and Frazzini 2008
DelBreadth	Breadth of ownership	Predictor	Chen, Hong and Stein 2002
EarningsForecastDisparity	Long-vs-short EPS forecasts	Predictor	Da and Warachka 2011
EarningsStreak	Earnings surprise streak	Predictor	Loh and Warachka 2012
EarningsSurprise	Earnings Surprise	Predictor	Foster, Olsen and Shevlin 1984
FirmAgeMom	Firm Age - Momentum	Predictor	Zhang 2006
High52	52 week high	Predictor	George and Hwang 2004
IndRetBig	Industry return of big firms	Predictor	Hou 2007
Mom12m	Momentum (12 month)	Predictor	Jegadeesh and Titman 1993

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Table B.4 – continued from previous page

Acronym	Description	Signal Type	Author
Mom12mOffSeason	Momentum without the seasonal part	Predictor	Heston and Sadka 2008
Mom6m	Momentum (6 month)	Predictor	Jegadeesh and Titman 1993
Mom6mJunk	Junk Stock Momentum	Predictor	Avramov et al 2007
NumEarnIncrease	Earnings streak length	Predictor	Loh and Warachka 2012
REV6	Earnings forecast revisions	Predictor	Chan, Jegadeesh and Lakonishok 1996
ResidualMomentum	Momentum based on FF3 residuals	Predictor	Blitz, Huij and Martens 2011
ResidualMomentum6m	6 month residual momentum	Placebo	Blitz, Huij and Martens 2011
RevenueSurprise	Revenue Surprise	Predictor	Jegadeesh and Livnat 2006
betaVIX	Systematic volatility	Predictor	Ang et al. 2006
iomom_cust	Customers momentum	Predictor	Menzly and Ozbas 2010
iomom_supp	Suppliers momentum	Predictor	Menzly and Ozbas 2010
retConglomerate	Conglomerate return	Predictor	Cohen and Lou 2012
		Profitability	
AnalystValue	Analyst Value	Predictor	Frankel and Lee 1998
CBOperProf	Cash-based operating profitability	Predictor	Ball et al. 2016
CBOperProfLagAT	Cash-based oper prof lagged assets	Placebo	Ball et al. 2016
CBOperProfLagAT_q	Cash-based oper prof lagged assets qtrly	Placebo	Ball et al. 2016
CompEquIss	Composite equity issuance	Predictor	Daniel and Titman 2006
ETR	Effective Tax Rate	Placebo	Abarbanell and Bushee 1998
EarningsConsistency	Earnings consistency	Predictor	Alwathainani 2009
FEPS	Analyst earnings per share	Predictor	Cen, Wei, and Zhang 2006
ForecastDispersion	EPS Forecast Dispersion	Predictor	Diether, Malloy and Scherbina 2002
GP	gross profits / total assets	Predictor	Novy-Marx 2013
GPlag	gross profits / total assets	Placebo	Novy-Marx 2013
GPlag_q	gross profits / total assets	Placebo	Novy-Marx 2013
MomSeason	Return seasonality years 2 to 5	Predictor	Heston and Sadka 2008
OperProf	operating profits / book equity	Predictor	Fama and French 2006
OperProfLag	operating profits / book equity	Placebo	Fama and French 2006
OperProfLag_q	operating profits / book equity	Placebo	Fama and French 2006
OperProfRD	Operating profitability R&D adjusted	Predictor	Ball et al. 2016
OperProfRDLagAT	Oper prof R&D adj lagged assets	Placebo	Ball et al. 2016
OperProfRDLagAT_q	Oper prof R&D adj lagged assets (qtrly)	Placebo	Ball et al. 2016
PM_q	Profit Margin	Placebo	Soliman 2008
RetNOA	Return on Net Operating Assets	Placebo	Soliman 2008
RetNOA_q	Return on Net Operating Assets	Placebo	Soliman 2008
Tax	Taxable income to income	Predictor	Lev and Nissim 2004
betaCR	Illiquidity-market return beta (beta4i)	Placebo	Acharya and Pedersen 2005
cashdebt	CF to debt	Placebo	Ou and Penman 1989
nanalyst	Number of analysts	Placebo	Elgers, Lo and Pfeiffer 2001
roaq	Return on assets (qtrly)	Predictor	Balakrishnan, Bartov and Faurel 2010
roic	Return on invested capital	Placebo	Brown and Rowe 2007
sfe	Earnings Forecast to price	Predictor	Elgers, Lo and Pfeiffer 2001
		Value	
AM	Total assets to market	Predictor	Fama and French 1992
AMq	Total assets to market (quarterly)	Placebo	Fama and French 1992
AssetLiquidityMarket	Asset liquidity over market	Placebo	Ortiz-Molina and Phillips 2014
AssetLiquidityMarketQuart	Asset liquidity over market (qtrly)	Placebo	Ortiz-Molina and Phillips 2014
BM	Book to market, original (Stattman 1980)	Predictor	Stattman 1980
BMdec	Book to market using December ME	Predictor	Fama and French 1992
BMq	Book to market (quarterly)	Placebo	Rosenberg, Reid, and Lanstein 1985
CashProd	Cash Productivity	Predictor	Chandrashekar and Rao 2009
Frontier	Efficient frontier index	Predictor	Nguyen and Swanson 2009
IntanBM	Intangible return using BM	Predictor	Daniel and Titman 2006
IntanCFP	Intangible return using CFtoP	Predictor	Daniel and Titman 2006
IntanEP	Intangible return using EP	Predictor	Daniel and Titman 2006
IntanSP	Intangible return using Sale2P	Predictor	Daniel and Titman 2006

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Acronym	Description	Signal Type	Author
LRreversal	Long-run reversal	Predictor	De Bondt and Thaler 1985
Leverage	Market leverage	Predictor	Bhandari 1988
Leverage_q	Market leverage quarterly	Placebo	Bhandari 1988
MRreversal	Medium-run reversal	Predictor	De Bondt and Thaler 1985
MomOffSeason	Off season long-term reversal	Predictor	Heston and Sadka 2008
MomOffSeason11YrPlus	Off season reversal years 11 to 15	Predictor	Heston and Sadka 2008
MomSeason06YrPlus	Return seasonality years 6 to 10	Predictor	Heston and Sadka 2008
MomSeason11YrPlus	Return seasonality years 11 to 15	Predictor	Heston and Sadka 2008
MomSeason16YrPlus	Return seasonality years 16 to 20	Predictor	Heston and Sadka 2008
RDS	Real dirty surplus	Predictor	Landsman et al. 2011
SP	Sales-to-price	Predictor	Barbee, Mukherji and Raines 1996
SP_q	Sales-to-price quarterly	Placebo	Barbee, Mukherji and Raines 1996
TrendFactor	Trend Factor	Predictor	Han, Zhou, Zhu 2016
ZScore	Altman Z-Score	Placebo	Dichev 1998
ZScore_q	Altman Z-Score quarterly	Placebo	Dichev 1998
	Volatility		
Activism2	Active shareholders	Predictor	Cremers and Nair 2005
BetaSquared	CAPM beta squred	Placebo	Fama and MacBeth 1973
FR	Pension Funding Status	Predictor	Franzoni and Marin 2006
FRbook	Pension Funding Status	Placebo	Franzoni and Marin 2006
FailureProbability	Failure probability	Placebo	Campbell, Hilscher and Szilagyi 2008
FailureProbabilityJune	Failure probability	Placebo	Campbell, Hilscher and Szilagyi 2008
IdioVol3F	Idiosyncratic risk (3 factor)	Predictor	Ang et al. 2006
IdioVolAHT	Idiosyncratic risk (AHT)	Predictor	Ali, Hwang, and Trombley 2003
IdioVolCAPM	Idiosyncratic risk (CAPM)	Placebo	Ang et al. 2006
IdioVolQF	Idiosyncratic risk (q factor)	Placebo	Ang et al. 2006
MaxRet	Maximum return over month	Predictor	Bali, Cakici, and Whitelaw 2011
PriceDelayTstat	Price delay SE adjusted	Predictor	Hou and Moskowitz 2005
RealizedVol	Realized (Total) Volatility	Predictor	Ang et al. 2006
ReturnSkew	Return skewness	Predictor	Bali, Engle and Murray 2015
ReturnSkew3F	Idiosyncratic skewness (3F model)	Predictor	Bali, Engle and Murray 2015
ReturnSkewCAPM	Idiosyncratic skewness (CAPM)	Placebo	Bali, Engle and Murray 2015
ReturnSkewQF	Idiosyncratic skewness (Q model)	Placebo	Bali, Engle and Murray 2015
VarCF	Cash-flow to price variance	Predictor	Haugen and Baker 1996
betaRC	Return-market illiquidity beta	Placebo	Acharya and Pedersen 2005
realestate	Real estate holdings	Predictor	Tuzel 2010

Table B.5: Conversion Returns for Single Anomaly Signals
We show equally-weighted long, short and long-short conversion returns of single anomalies. The signals are sorted into 10 groups. Standard errors are adjusted according to Newey and West (1987). The sample covers the period from January 1996 to June 2021.

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
			Accruals			
AbnormalAccruals	0.38	3.74	0.38	3.72	0.00	1.09
AbnormalAccrualsPercent	0.20	2.10	0.19	2.04	0.01	4.02
Accruals	0.14	1.22	0.13	1.15	0.01	6.03
AssetGrowth	0.62	3.74	0.61	3.71	0.01	2.80
AssetGrowth_q	0.79	4.39	0.80	4.42	-0.01	-2.86
ChAssetTurnover	-0.04	-0.40	-0.04	-0.45	0.00	2.66
ChEQ	0.68	4.42	0.68	4.43	-0.00	-1.20
ChNCOA	0.60	4.51	0.59	4.44	0.01	5.66
ChNCOL	0.20	1.55	0.20	1.53	0.00	1.86
ChNNCOA	0.21	2.10	0.21	2.10	0.00	0.48
ChNWC	0.11	1.29	0.11	1.26	0.00	2.48
ChPM	0.16	1.41	0.15	1.38	0.00	2.37
ChangeInRecommendation	0.01	0.15	0.02	0.19	-0.00	-2.44
Coskewness	0.25	1.43	0.24	1.39	0.01	4.25
DelCOA	0.23	1.84	0.23	1.78	0.01	5.26
DelCOL	-0.08	-0.58	-0.09	-0.62	0.01	4.29
DelEqu	0.77	4.76	0.77	4.77	-0.00	-1.32
GrAdExp	0.21	1.15	0.20	1.13	0.00	1.24
GrSaleToGrOverhead	-0.04	-0.30	-0.04	-0.33	0.00	2.94
GrSaleToGrReceivables	0.10	0.93	0.10	0.95	-0.00	-1.24
IntMom	-0.18	-0.84	-0.21	-0.95	0.02	11.65
LaborforceEfficiency	-0.09	-0.93	-0.10	-0.95	0.00	1.23
MomSeasonShort	-0.55	-3.43	-0.56	-3.47	0.01	4.26
PS	0.27	0.85	0.23	0.73	0.04	6.62
PctAcc	0.35	3.19	0.33	3.02	0.02	11.82
PctTotAcc	0.31	3.05	0.30	2.96	0.01	6.98
TotalAccruals	0.38	3.17	0.38	3.19	-0.00	-2.04
dNoa	0.60	4.42	0.59	4.35	0.01	5.33
hire	0.28	1.74	0.27	1.66	0.01	8.11
saleinv	0.28	2.40	0.27	2.29	0.01	9.08
			Beta			
AdExp	0.20	0.64	0.24	0.75	-0.04	-12.01
AssetTurnover	0.66	4.13	0.64	4.04	0.01	8.74
AssetTurnover_q	0.47	2.67	0.46	2.60	0.01	7.50

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Table B.5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
Beta	0.26	0.68	0.28	0.75	-0.03	-14.85
BetaFP	0.25	0.62	0.26	0.65	-0.01	-6.02
BetaLiquidityPS	0.12	0.74	0.11	0.72	0.00	1.12
BetaTailRisk	0.32	1.34	0.33	1.39	-0.01	-6.41
BrandCapital	0.52	2.92	0.55	3.05	-0.02	-8.59
CapTurnover	0.30	1.47	0.29	1.45	0.00	1.69
CapTurnover_q	0.48	2.18	0.48	2.17	0.00	2.12
DelLTI	0.29	3.24	0.28	3.21	0.00	1.74
DelSTI	-0.04	-0.35	-0.04	-0.34	-0.00	-1.46
DownsideBeta	0.04	0.12	0.06	0.15	-0.01	-6.03
ForecastDispersionLT	0.13	0.65	0.14	0.70	-0.01	-6.14
GrLTNOA	-0.06	-0.62	-0.07	-0.66	0.00	2.53
OPLeverage	0.59	3.67	0.59	3.71	-0.01	-4.49
OPLeverage_q	0.58	3.68	0.59	3.74	-0.01	-7.36
OrgCap	0.57	4.22	0.57	4.21	0.00	0.15
OrgCapNoAdj	0.68	2.91	0.69	2.95	-0.01	-5.29
betaRR	0.34	0.99	0.35	1.02	-0.01	-6.92
		Intangibles				
AssetLiquidityBook	0.30	1.16	0.31	1.23	-0.02	-9.49
AssetLiquidityBookQuart	0.19	0.67	0.21	0.73	-0.02	-10.21
BPEBM	-0.04	-0.43	-0.04	-0.40	-0.00	-2.48
BookLeverage	0.01	0.04	0.03	0.12	-0.02	-10.58
BookLeverageQuarterly	-0.10	-0.43	-0.08	-0.36	-0.02	-8.16
Cash	0.42	1.36	0.43	1.39	-0.01	-4.79
EBM	-0.10	-0.87	-0.09	-0.79	-0.01	-6.13
EBM_q	-0.03	-0.26	-0.02	-0.18	-0.01	-6.00
Herf	0.55	2.26	0.56	2.28	-0.00	-3.05
HerfAsset	0.32	1.31	0.33	1.33	-0.01	-3.98
HerfBE	0.32	1.41	0.32	1.41	-0.00	-0.19
KZ	-0.14	-0.88	-0.15	-0.92	0.01	4.13
KZ_q	-0.14	-0.74	-0.15	-0.79	0.01	5.76
NOA	0.72	4.70	0.71	4.64	0.01	5.27
NetDebtPrice	0.17	0.50	0.14	0.41	0.03	8.17
NetDebtPrice_q	0.29	0.87	0.26	0.76	0.04	8.95
OrderBacklog	-0.17	-0.93	-0.16	-0.89	-0.01	-2.32
RD	1.01	3.36	0.99	3.31	0.01	4.73
RD_q	1.12	3.35	1.11	3.31	0.01	4.53
depr	0.37	1.95	0.36	1.91	0.01	4.57

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Table B.5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
pchdepr	0.06	0.59	0.06	0.59	0.00	0.09
rd_sale	0.48	1.26	0.50	1.32	-0.03	-9.44
rd_sale_q	0.36	1.00	0.39	1.07	-0.02	-8.63
tang	0.33	1.19	0.35	1.25	-0.02	-7.85
tang_q	0.38	1.88	0.39	1.92	-0.01	-4.16
			Investment			
AccrualQuality	-0.04	-0.19	-0.02	-0.09	-0.02	-11.92
BetaBDLeverage	0.03	0.17	0.03	0.22	-0.01	-5.41
CF	-0.11	-0.39	-0.14	-0.47	0.02	10.05
CFq	-0.13	-0.45	-0.16	-0.57	0.03	14.46
ChInv	0.32	2.72	0.31	2.65	0.01	5.52
ChInvIA	0.31	2.40	0.30	2.32	0.01	6.27
DelFINL	0.09	0.80	0.08	0.69	0.01	9.91
DelNetFin	0.16	1.34	0.14	1.24	0.01	8.98
DelayAcct	-0.28	-1.71	-0.27	-1.63	-0.01	-6.26
EPq	0.02	0.09	0.02	0.12	-0.01	-2.95
EntMult	0.35	1.34	0.35	1.33	0.00	0.59
EntMult_q	0.08	0.33	0.07	0.30	0.01	4.00
ExclExp	0.13	1.37	0.13	1.36	0.00	1.01
GrGMToGrSales	0.35	3.47	0.34	3.37	0.01	6.32
GrSaleToGrInv	0.13	1.23	0.12	1.15	0.01	5.85
InvGrowth	0.27	1.74	0.25	1.64	0.02	9.02
InvestPPEInv	0.51	3.69	0.50	3.60	0.01	8.45
Investment	0.41	3.31	0.41	3.33	-0.00	-2.02
MomOffSeason16YrPlus	-0.10	-0.74	-0.10	-0.74	-0.00	-0.31
NetDebtFinance	0.17	1.38	0.15	1.28	0.01	10.18
cfp	0.13	0.47	0.10	0.38	0.03	10.84
cfpq	0.22	1.16	0.20	1.07	0.02	9.13
grcapx	0.49	3.55	0.48	3.50	0.01	4.28
grcapx1y	0.26	2.39	0.25	2.33	0.01	3.68
grcapx3y	0.47	3.61	0.47	3.59	0.00	1.92
pchgm_pchsale	0.21	1.95	0.20	1.87	0.01	4.99
pchsaleinv	0.02	0.17	0.01	0.13	0.00	3.09
			Issuance			
AOP	0.20	1.47	0.20	1.46	0.00	1.02
AnalystRevision	0.09	0.74	0.09	0.73	0.00	0.71
CompositeDebtIssuance	0.02	0.23	0.02	0.14	0.01	6.33
EP	0.02	0.09	0.03	0.12	-0.01	-3.63

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Table B.5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
EquityDuration	-0.08	-0.36	-0.11	-0.47	0.03	12.28
IntrinsicValue	0.04	0.19	0.03	0.13	0.01	5.07
MomOffSeason06YrPlus	0.28	2.10	0.27	2.05	0.01	3.16
NetEquityFinance	0.33	1.40	0.30	1.29	0.03	13.86
NetPayoutYield	0.60	2.59	0.58	2.50	0.02	8.25
OrderBacklogChg	0.01	0.06	-0.00	-0.01	0.02	5.98
PM	-0.15	-0.62	-0.18	-0.74	0.03	15.29
PayoutYield_q	0.40	3.07	0.41	3.10	-0.00	-2.72
PredictedFE	-0.10	-0.46	-0.10	-0.48	0.00	2.07
RoE	0.17	0.88	0.15	0.77	0.02	11.15
ShareIss1Y	0.70	3.62	0.68	3.47	0.03	16.36
ShareIss5Y	0.48	2.53	0.46	2.41	0.02	11.97
XFIN	0.33	1.23	0.29	1.10	0.03	16.75
		Liquidity				
Activism1	0.08	0.28	0.08	0.28	-0.00	-0.45
BidAskSpread	0.01	0.03	0.08	0.20	-0.07	-19.40
DelayNonAcct	0.15	0.78	0.17	0.89	-0.02	-11.06
DolVol	0.18	0.82	0.23	1.01	-0.04	-10.85
EarnSupBig	-0.26	-1.03	-0.27	-1.07	0.01	3.31
FirmAge	-0.02	-0.09	0.04	0.15	-0.06	-32.43
Illiquidity	0.31	1.14	0.38	1.40	-0.07	-18.71
IndMom	0.74	2.74	0.74	2.73	0.00	0.80
PriceDelayRsq	-0.16	-0.88	-0.11	-0.59	-0.05	-29.60
PriceDelaySlope	-0.18	-1.47	-0.15	-1.25	-0.03	-15.78
ShortInterest	0.17	1.02	0.08	0.47	0.09	33.75
VolMkt	-0.07	-0.20	-0.11	-0.31	0.04	16.07
VolSD	0.19	0.92	0.19	0.94	-0.00	-1.31
VolumeTrend	0.31	1.73	0.28	1.56	0.03	13.28
WW	0.06	0.20	0.12	0.39	-0.06	-23.30
WW_Q	0.31	1.06	0.37	1.25	-0.06	-23.14
betaCC	-0.27	-1.52	-0.25	-1.40	-0.02	-10.90
betaNet	0.04	0.18	0.07	0.30	-0.02	-11.19
secured	0.01	0.14	0.02	0.27	-0.01	-9.41
zerotrade12M	-0.11	-0.41	-0.14	-0.51	0.03	13.08
zerotrade1M	-0.20	-0.71	-0.23	-0.80	0.03	11.82
zerotrade6M	-0.20	-0.67	-0.23	-0.78	0.03	14.69
		Momentum				
AnnouncementReturn	0.17	1.45	0.17	1.43	0.00	1.34

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Table B.5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
ChTax	-0.27	-2.21	-0.28	-2.26	0.01	4.97
ChangeRoA	-0.30	-2.21	-0.31	-2.29	0.01	7.19
ChangeRoE	-0.26	-2.35	-0.27	-2.45	0.01	7.24
CoskewACX	0.57	2.70	0.56	2.65	0.01	5.61
CustomerMomentum	-0.10	-0.44	-0.11	-0.45	0.00	0.83
DelBreadth	0.55	2.70	0.56	2.72	-0.01	-4.01
EarningsForecastDisparity	-0.22	-1.19	-0.22	-1.22	0.01	3.32
EarningsStreak	0.00	0.00	-0.02	-0.12	0.02	8.89
EarningsSurprise	-0.37	-3.64	-0.38	-3.69	0.01	3.85
FirmAgeMom	1.76	4.57	1.75	4.55	0.01	2.18
High52	0.16	0.40	0.13	0.32	0.03	13.24
IndRetBig	0.32	1.18	0.33	1.19	-0.01	-1.91
Mom12m	0.40	1.13	0.38	1.06	0.03	11.67
Mom12mOffSeason	0.64	1.94	0.63	1.91	0.01	5.35
Mom6m	0.74	2.26	0.73	2.22	0.01	6.66
Mom6mJunk	0.80	2.05	0.78	2.00	0.02	5.68
NumEarnIncrease	-0.03	-0.34	-0.05	-0.54	0.02	20.41
REV6	-0.12	-0.60	-0.13	-0.67	0.02	7.86
ResidualMomentum	0.35	1.78	0.34	1.75	0.01	3.83
ResidualMomentum6m	0.37	2.11	0.37	2.10	0.00	0.71
RevenueSurprise	0.04	0.38	0.04	0.35	0.00	2.80
betaVIX	0.31	2.07	0.31	2.07	0.00	0.40
iomom_cust	-0.28	-1.56	-0.28	-1.56	0.00	1.17
iomom_supp	0.22	1.17	0.22	1.17	-0.00	-1.16
retConglomerate	0.29	1.58	0.30	1.59	-0.00	-1.26
		Profitability				
AnalystValue	-0.22	-0.80	-0.23	-0.86	0.01	6.55
CBOperProf	0.69	3.20	0.65	3.02	0.04	18.50
CBOperProfLagAT	0.58	3.17	0.55	2.99	0.03	16.26
CBOperProfLagAT_q	0.41	2.58	0.39	2.43	0.02	12.79
CompEquIss	0.23	1.40	0.21	1.31	0.01	8.92
ETR	-0.18	-1.74	-0.18	-1.77	0.00	1.89
EarningsConsistency	-0.20	-1.32	-0.20	-1.35	0.00	1.76
FEPS	-0.03	-0.08	-0.08	-0.26	0.06	24.59
ForecastDispersion	0.03	0.16	0.00	0.00	0.03	18.65
GP	0.47	1.74	0.45	1.67	0.02	9.24
GPlag	0.23	1.05	0.22	1.02	0.01	4.26
GPlag_q	0.23	1.01	0.22	0.97	0.01	5.84

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Table B.5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
MomSeason	-0.19	-1.54	-0.20	-1.57	0.00	3.10
OperProf	0.20	0.90	0.17	0.79	0.03	13.48
OperProfLag	-0.14	-0.80	-0.16	-0.92	0.02	10.69
OperProfLag_q	0.21	0.99	0.18	0.87	0.03	14.85
OperProfRD	0.44	1.76	0.39	1.59	0.04	19.50
OperProfRDLagAT	0.35	1.75	0.32	1.59	0.03	13.83
OperProfRDLagAT_q	0.62	2.72	0.58	2.54	0.04	18.67
PM_q	0.07	0.32	0.05	0.20	0.03	14.91
RetNOA	0.04	0.33	0.03	0.26	0.01	5.10
RetNOA_q	0.05	0.28	0.03	0.17	0.02	10.57
Tax	0.32	1.86	0.29	1.73	0.02	13.74
betaCR	-0.05	-0.33	-0.08	-0.46	0.02	9.80
cashdebt	-0.09	-0.42	-0.11	-0.51	0.02	10.15
nanalyst	0.23	1.35	0.17	1.01	0.06	23.48
roaq	-0.12	-0.50	-0.15	-0.63	0.03	14.78
roic	-0.03	-0.12	-0.05	-0.21	0.02	10.98
sfe	-0.60	-1.54	-0.64	-1.62	0.03	6.75
		Value				
AM	-0.04	-0.12	-0.05	-0.14	0.01	3.59
AMq	-0.17	-0.51	-0.18	-0.54	0.01	3.78
AssetLiquidityMarket	0.14	0.71	0.14	0.69	0.00	1.30
AssetLiquidityMarketQuart	0.15	0.67	0.15	0.69	-0.01	-2.37
BM	0.17	0.79	0.18	0.81	-0.01	-2.17
BMdec	-0.08	-0.38	-0.08	-0.39	0.00	0.77
BMq	-0.15	-0.48	-0.15	-0.47	-0.00	-1.27
CashProd	0.06	0.28	0.05	0.27	0.00	0.82
Frontier	0.04	0.15	0.04	0.16	-0.00	-1.09
IntanBM	0.23	0.80	0.25	0.85	-0.02	-7.27
IntanCFP	0.37	1.37	0.38	1.41	-0.01	-5.97
IntanEP	0.29	1.19	0.30	1.23	-0.01	-4.82
IntanSP	0.49	1.69	0.52	1.82	-0.04	-14.05
LRreversal	0.32	1.37	0.34	1.47	-0.02	-10.77
Leverage	0.04	0.11	0.03	0.09	0.01	4.15
Leverage_q	0.03	0.08	0.02	0.06	0.01	3.23
MRreversal	0.31	1.44	0.32	1.51	-0.02	-7.89
MomOffSeason	0.36	1.61	0.36	1.62	-0.00	-1.62
MomOffSeason11YrPlus	0.36	2.57	0.37	2.63	-0.01	-4.24
MomSeason06YrPlus	0.20	1.71	0.19	1.67	0.00	2.50

Continued on next page

Table B.5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
MomSeason11YrPlus	0.12	0.99	0.12	0.94	0.01	3.19
MomSeason16YrPlus	0.58	4.70	0.58	4.67	0.00	2.08
RDS	0.23	2.19	0.24	2.25	-0.01	-5.52
SP	0.26	0.76	0.25	0.74	0.01	3.97
SP_q	0.30	0.90	0.30	0.88	0.01	2.91
TrendFactor	0.30	1.32	0.30	1.31	0.00	1.15
ZScore	0.14	0.51	0.15	0.53	-0.01	-2.41
ZScore_q	0.43	1.53	0.45	1.59	-0.02	-5.67
		Volatility				
BetaSquared	-0.19	-0.51	-0.22	-0.58	0.03	15.60
FR	-0.47	-2.78	-0.48	-2.86	0.01	6.32
FRbook	-0.19	-1.55	-0.19	-1.54	-0.00	-0.85
FailureProbability	-0.29	-0.71	-0.35	-0.86	0.06	21.50
FailureProbabilityJune	-0.03	-0.09	-0.09	-0.26	0.06	22.76
IdioVol3F	0.23	0.65	0.17	0.48	0.06	28.24
IdioVolAHT	-0.02	-0.06	-0.12	-0.28	0.09	32.47
IdioVolCAPM	0.15	0.42	0.09	0.26	0.06	26.65
IdioVolQF	0.44	1.27	0.38	1.09	0.06	27.52
MaxRet	0.21	0.64	0.16	0.50	0.05	24.06
PriceDelayTstat	0.00	0.03	-0.00	-0.02	0.01	5.39
RealizedVol	0.16	0.42	0.11	0.28	0.05	23.44
ReturnSkew	-0.02	-0.26	-0.04	-0.39	0.01	9.88
ReturnSkew3F	-0.18	-1.98	-0.19	-2.10	0.01	9.07
ReturnSkewCAPM	-0.09	-0.99	-0.10	-1.11	0.01	9.68
ReturnSkewQF	-0.15	-1.69	-0.16	-1.79	0.01	7.48
VarCF	-0.19	-0.78	-0.21	-0.89	0.03	13.60
betaRC	-0.39	-1.83	-0.40	-1.88	0.01	6.89
realestate	0.06	0.51	0.05	0.42	0.01	5.31

Table B.6: Semivariance Premia for Single Anomaly Signals
We show equally-weighted long, short and long-short semivariance premia of single anomalies. The signals are sorted into 10 groups. The sample covers the period from January 1996 to June 2021.

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
		Accurals		
AbnormalAccruals	-0.15	-8.53	0.18	12.38
AbnormalAccrualsPercent	0.35	22.91	-0.11	-15.78
Accruals	-0.08	-5.08	-0.02	-1.29
AssetGrowth	-0.19	-9.29	0.31	11.05
AssetGrowth_q	-0.25	-10.40	0.35	15.04
ChAssetTurnover	-0.05	-3.01	0.02	2.49
ChEQ	-0.24	-10.06	0.29	12.87
ChNCOA	-0.20	-10.92	0.19	13.17
ChNCOL	-0.21	-9.34	0.16	10.40
ChNNCOA	-0.09	-4.57	0.13	8.48
ChNWC	-0.02	-1.29	-0.02	-1.82
ChPM	0.02	0.74	-0.10	-10.17
ChangeInRecommendation	0.03	2.01	-0.01	-0.89
Coskewness	0.00	0.07	-0.22	-11.56
DelCOA	-0.16	-10.66	0.05	4.55
DelCOL	-0.15	-9.46	0.08	6.14
DelEqu	-0.24	-11.09	0.40	14.01
GrAdExp	-0.06	-2.33	-0.03	-2.30
GrSaleToGrOverhead	-0.06	-3.90	-0.02	-1.47
GrSaleToGrReceivables	-0.02	-1.55	0.10	8.57
IntMom	0.28	8.61	-0.45	-15.26
LaborforceEfficiency	-0.01	-0.52	0.00	0.01
MomSeasonShort	0.11	4.44	-0.18	-8.45
PS	0.30	7.81	-0.53	-21.24
PctAcc	0.19	10.84	-0.20	-21.56
PctTotAcc	-0.04	-3.13	0.02	2.87
TotalAccruals	-0.37	-20.64	0.51	22.84
dNoa	-0.16	-8.70	0.28	16.87
hire	-0.06	-2.41	-0.01	-0.73
saleinv	0.48	27.54	-0.37	-23.71
		Beta		
AdExp	0.02	0.65	0.27	10.15
AssetTurnover	0.15	5.78	-0.46	-14.65
AssetTurnover_q	0.16	6.26	-0.52	-15.34
Beta	-1.17	-40.74	0.92	24.65

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Table B.6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
BetaFP	-1.51	-45.48	0.54	18.50
BetaLiquidityPS	-0.13	-5.74	-0.07	-3.81
BetaTailRisk	-0.77	-35.14	0.46	21.65
BrandCapital	-0.05	-2.28	-0.05	-2.40
CapTurnover	0.45	23.88	-0.70	-19.41
CapTurnover_q	0.47	28.45	-0.86	-21.57
DelLTI	-0.06	-4.52	0.11	8.18
DelSTI	-0.02	-1.08	0.09	7.67
DownsideBeta	-1.21	-35.24	0.47	14.38
ForecastDispersionLT	-0.55	-26.56	0.23	12.60
GrLTNOA	-0.08	-4.67	-0.06	-3.94
OPLeverage	0.25	14.99	0.15	11.02
OPLeverage_q	0.23	16.01	0.14	10.78
OrgCap	-0.28	-15.69	0.40	17.45
OrgCapNoAdj	-0.07	-2.09	0.62	23.62
betaRR	-1.18	-44.31	0.66	18.76
		Intangibles		
AssetLiquidityBook	-0.54	-22.85	1.16	25.10
AssetLiquidityBookQuart	-0.49	-24.50	1.15	26.69
BPEBM	-0.16	-7.84	0.12	8.49
BookLeverage	-0.00	-0.12	0.66	25.58
BookLeverageQuarterly	0.02	0.82	0.64	24.93
Cash	-0.49	-22.16	1.09	27.33
EBM	-0.30	-16.86	0.26	25.51
EBM_q	-0.31	-19.87	0.25	27.04
Herf	-0.48	-19.13	0.61	19.70
HerfAsset	-0.39	-20.11	0.62	20.73
HerfBE	-0.27	-12.65	0.54	19.47
KZ	0.19	7.91	-0.04	-1.66
KZ_q	0.06	2.60	0.33	14.66
NOA	-0.39	-21.64	0.68	17.81
NetDebtPrice	0.39	7.60	0.42	10.90
NetDebtPrice_q	0.55	12.13	0.29	7.83
OrderBacklog	-0.01	-0.22	0.28	16.75
RD	-0.71	-23.08	1.21	28.13
RD_q	-0.61	-19.49	1.28	28.02
depr	-0.28	-11.49	0.32	18.31
pchdepr	-0.08	-3.30	0.06	5.24

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Table B.6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
rd_sale	-0.89	-34.81	1.80	32.74
rd_sale_q	-0.80	-26.64	1.71	31.63
tang	-0.58	-27.43	1.39	29.95
tang_q	-0.36	-16.21	0.72	23.77
		Investment		
AccrualQuality	-0.50	-40.06	0.97	28.05
BetaBDLeverage	0.14	5.14	0.07	4.23
CF	0.53	14.85	-1.18	-29.94
CFq	0.50	16.16	-1.20	-35.27
ChInv	-0.15	-11.16	0.06	6.87
ChInvIA	-0.04	-2.32	0.07	3.23
DelFINL	0.10	7.04	-0.05	-4.15
DelNetFin	-0.02	-1.41	-0.04	-3.68
DelayAcct	-0.31	-16.34	0.55	16.54
EPq	-0.05	-2.16	0.05	2.84
EntMult	0.13	4.31	0.10	4.88
EntMult_q	0.19	6.06	-0.01	-0.52
ExclExp	0.13	7.89	-0.03	-2.62
GrGMToGrSales	0.05	2.58	-0.21	-15.52
GrSaleToGrInv	-0.05	-3.13	0.03	2.69
InvGrowth	-0.08	-4.76	-0.04	-2.68
InvestPPEInv	-0.09	-5.33	0.11	7.67
Investment	-0.17	-8.91	0.25	16.21
MomOffSeason16YrPlus	0.10	6.96	0.07	5.49
NetDebtFinance	0.05	3.20	-0.06	-5.42
cfp	0.31	8.72	-1.19	-28.02
cfpq	0.26	9.94	-0.85	-27.63
grcapx	-0.11	-4.35	0.14	7.49
grcapx1y	-0.03	-1.43	0.09	6.40
grcapx3y	-0.13	-5.75	0.30	12.00
pchgm_pchsale	0.11	6.52	-0.21	-15.45
pchsaleinv	-0.01	-0.55	-0.02	-1.44
		Issuance		
AOP	0.09	5.00	-0.07	-6.73
AnalystRevision	0.06	3.90	-0.04	-3.43
CompositeDebtIssuance	-0.16	-8.26	0.01	0.89
EP	-0.09	-3.29	0.06	3.81
EquityDuration	0.52	18.70	-0.90	-28.44

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Table B.6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
IntrinsicValue	0.53	27.00	-0.63	-30.51
MomOffSeason06YrPlus	-0.13	-5.11	0.20	10.81
NetEquityFinance	0.62	37.36	-1.22	-25.06
NetPayoutYield	0.51	18.81	-1.12	-23.70
OrderBacklogChg	-0.02	-1.13	-0.03	-1.55
PM	0.78	37.97	-1.45	-28.44
PayoutYield_q	0.49	17.80	-0.24	-19.81
PredictedFE	0.23	5.84	-0.18	-12.62
RoE	0.66	32.51	-1.11	-30.97
ShareIss1Y	0.55	28.03	-0.97	-22.92
ShareIss5Y	0.86	28.68	-0.96	-20.74
XFIN	0.57	24.96	-1.28	-25.54
		Liquidity		
Activism1	0.09	3.23	0.16	9.98
BidAskSpread	-1.16	-32.19	1.98	31.48
DelayNonAcct	0.13	6.95	0.36	19.88
DolVol	0.40	15.97	1.69	28.40
EarnSupBig	0.08	3.65	-0.11	-4.23
FirmAge	-0.38	-13.85	0.89	28.06
Illiquidity	0.05	2.63	2.04	29.10
IndMom	0.07	2.59	0.10	3.65
PriceDelayRsq	-0.03	-1.19	1.10	28.50
PriceDelaySlope	-0.19	-12.85	0.57	21.65
ShortInterest	0.59	25.66	-0.36	-18.68
VolMkt	1.30	37.35	-0.50	-11.01
VolSD	1.37	59.58	0.37	16.28
VolumeTrend	0.35	12.68	-0.36	-11.84
WW	-0.18	-10.13	1.83	29.16
WW_Q	-0.15	-7.62	1.83	30.64
betaCC	0.04	2.59	1.00	20.88
betaNet	-0.20	-12.66	1.17	18.93
secured	-0.11	-11.39	0.23	20.02
zerotrade12M	1.14	36.57	-0.19	-5.89
zerotrade1M	1.09	36.73	-0.16	-4.91
zerotrade6M	1.16	37.49	-0.23	-7.11
		Momentum		
AnnouncementReturn	0.11	6.48	-0.12	-8.83
ChTax	0.03	2.37	-0.10	-12.13

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Table B.6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
ChangeRoA	0.03	1.70	-0.15	-9.42
ChangeRoE	0.04	1.99	-0.16	-10.59
CoskewACX	-0.03	-1.15	-0.24	-7.32
CustomerMomentum	0.01	0.36	-0.10	-4.51
DelBreadth	0.04	1.60	-0.06	-4.03
EarningsForecastDisparity	0.03	1.18	-0.12	-8.02
EarningsStreak	0.07	3.47	-0.28	-15.36
EarningsSurprise	0.01	0.71	-0.02	-1.67
FirmAgeMom	0.03	0.54	-0.28	-7.68
High52	0.98	22.46	-1.14	-24.64
IndRetBig	0.05	1.77	0.10	3.18
Mom12m	0.52	10.98	-0.67	-19.11
Mom12mOffSeason	0.17	4.06	-0.29	-8.83
Mom6m	0.38	8.88	-0.50	-14.76
Mom6mJunk	0.62	12.58	-0.54	-14.14
NumEarnIncrease	0.11	12.02	-0.23	-24.24
REV6	0.06	2.92	-0.04	-1.44
ResidualMomentum	0.08	3.28	-0.12	-7.64
ResidualMomentum6m	0.09	4.14	-0.12	-8.05
RevenueSurprise	0.00	0.01	-0.01	-0.89
betaVIX	0.16	7.57	-0.06	-2.65
iomom_cust	0.04	2.02	-0.08	-3.09
iomom_supp	0.03	1.55	-0.00	-0.05
retConglomerate	0.06	2.77	-0.03	-2.01
		Profitability		
AnalystValue	0.46	18.13	-0.82	-32.44
CBOperProf	0.57	26.66	-1.45	-24.41
CBOperProfLagAT	0.48	23.59	-1.42	-23.95
CBOperProfLagAT_q	0.34	19.41	-1.03	-24.33
CompEquIss	0.19	5.11	-0.74	-18.29
ETR	0.14	7.02	-0.11	-11.04
EarningsConsistency	0.46	19.33	-0.47	-23.05
FEPS	0.83	32.89	-1.75	-38.57
ForecastDispersion	0.70	41.31	-0.71	-32.56
GP	0.69	31.11	-1.40	-27.24
GPlag	0.61	23.61	-1.14	-22.44
GPlag_q	0.60	28.51	-1.23	-28.27
MomSeason	0.12	6.23	-0.16	-8.06

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Table B.6 – continued from previous page

Acronym	VP^{+}_{ls}	t	VP^{-}_{ls}	t
OperProf	0.72	29.25	-0.77	-31.00
OperProfLag	0.66	32.42	-0.73	-32.88
OperProfLag_q	0.64	28.86	-1.24	-39.21
OperProfRD	0.65	23.81	-1.47	-24.30
OperProfRDLagAT	0.52	21.80	-1.26	-22.10
OperProfRDLagAT_q	0.51	22.91	-1.39	-24.75
PM_q	0.65	32.72	-1.47	-28.72
RetNOA	0.11	5.12	-0.26	-15.89
RetNOA_q	0.35	21.47	-0.60	-26.46
Tax	0.45	26.60	-0.96	-34.65
betaCR	0.04	2.47	-0.83	-15.04
cashdebt	0.77	39.64	-1.56	-27.80
nanalyst	-0.02	-1.11	-1.33	-32.15
roaq	0.73	32.13	-1.69	-28.91
roic	0.77	37.57	-1.61	-29.37
sfe	0.60	13.62	-1.58	-31.60
		Value		
AM	-0.37	-8.42	-0.11	-4.74
AMq	-0.37	-8.70	-0.11	-4.97
AssetLiquidityMarket	-0.22	-7.42	0.44	12.09
AssetLiquidityMarketQuart	-0.21	-6.40	0.44	14.43
BM	-0.38	-10.07	0.28	10.73
BMdec	0.06	1.87	-0.12	-7.34
BMq	-0.32	-8.50	0.25	11.29
CashProd	-0.15	-7.38	0.19	12.56
Frontier	-0.28	-7.58	0.55	21.82
IntanBM	-0.46	-13.61	0.40	14.84
IntanCFP	-0.26	-6.47	0.12	4.49
IntanEP	-0.19	-5.66	0.16	6.98
IntanSP	-0.83	-20.28	0.89	26.03
LRreversal	-0.50	-14.53	0.69	16.95
Leverage	-0.34	-7.96	-0.31	-12.52
Leverage_q	-0.32	-7.46	-0.31	-12.68
MRreversal	-0.23	-7.96	0.40	12.75
MomOffSeason	-0.20	-6.16	0.22	7.64
MomOffSeason11YrPlus	-0.09	-5.31	0.30	19.43
MomSeason06YrPlus	0.06	3.54	-0.13	-9.10
MomSeason11YrPlus	0.03	2.02	-0.14	-10.80

Continued on next page

Table B.6 – continued from previous page

Acronym	VP^{+}_{ls}	t	VP^{-}_{ls}	t
MomSeason16YrPlus	-0.04	-2.40	-0.08	-6.22
RDS	-0.16	-7.60	0.30	20.28
SP	0.08	2.22	-0.77	-18.79
SP_q	0.12	3.64	-0.84	-19.92
TrendFactor	-0.06	-2.13	-0.00	-0.13
ZScore	-0.45	-11.26	0.78	17.09
ZScore_q	-0.73	-20.25	0.72	18.19
		Volatility		
BetaSquared	1.17	44.02	-0.96	-24.77
FR	0.49	16.19	-0.30	-15.66
FRbook	0.15	8.08	-0.12	-12.05
FailureProbability	1.62	36.71	-1.80	-31.96
FailureProbabilityJune	1.26	38.77	-1.66	-30.59
IdioVol3F	1.26	32.91	-1.69	-28.33
IdioVolAHT	1.52	34.72	-2.19	-30.38
IdioVolCAPM	1.31	33.52	-1.73	-28.07
IdioVolQF	1.24	32.01	-1.50	-36.03
MaxRet	1.12	32.47	-1.41	-27.35
PriceDelayTstat	0.28	29.25	-0.14	-17.21
RealizedVol	1.43	32.81	-1.64	-28.35
ReturnSkew	0.13	9.13	-0.33	-16.33
ReturnSkew3F	0.09	7.10	-0.26	-15.11
ReturnSkewCAPM	0.10	8.10	-0.27	-15.32
ReturnSkewQF	0.08	6.62	-0.20	-19.74
VarCF	1.22	35.48	-1.14	-22.09
betaRC	0.56	21.51	-0.53	-15.36
realestate	-0.10	-6.12	-0.17	-8.26

B.3 Cluster Algorithm

We form groups based on the similarity of the information provided by the anomaly signals. To do this, we first transform all signals so that a high signal corresponds to a high expected return. Then, for each month, we compute the cross-sectional ranks of the signals and scale them to the interval $[0, 1]$. Finally, we calculate pairwise correlations of signal ranks in our sample of optionable stocks between 1996 and 2021.

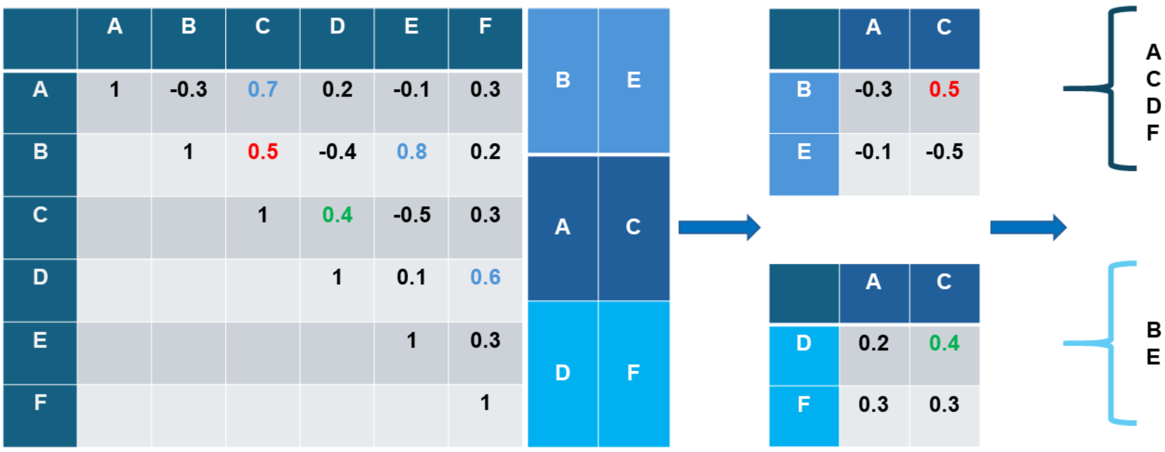
To group the signals, we iterate over all signal pairs, starting with the pair with the highest correlation and proceeding in descending order. In general, signals with high correlation are grouped into the same cluster. More specifically, each signal initially belongs to a separate cluster. During the iteration, two clusters are merged if all pairwise correlations within signals in the two candidate clusters exceed 0.2. In the second step, we rerun the algorithm with the criterion that the average correlation between signals in the two clusters must be greater than 0, and any newly formed cluster must not exceed 40 signals. The algorithm terminates when 10 clusters have been created.

We illustrate our anomaly clustering method using a simple example. Consider a small set of anomalies consisting of only six signals: $A, B, \ldots, F$ and assume we terminate the algorithm as soon as two clusters were formed. First, we compute the correlation matrix among all anomaly signals. Figure B.4 gives an example of such a correlation matrix.

We then sort these correlations in descending order. Each characteristic initially represents a distinct cluster. We iteratively merge these clusters based on the pairwise correlations of its members. Here, the highest pairwise correlations are 0.8, 0.7, and 0.6, marked in blue. Accordingly, in the first three steps, we form clusters $\{B, E\}$, $\{A, C\}$ and $\{D, F\}$. The next highest pairwise correlation is 0.5 between signals B and C, marked in red in Figure B.4. Therefore, the algorithm checks if the two clusters B and C are in, that is $\{B, E\}$ and $\{A, C\}$, should be merged. However, since there are pairwise correlations below 0.2, the clusters are not merged. Even in the second iteration of the algorithm, the clusters were not merged, since the average pairwise correlation is below zero.

The algorithm thus keeps the three clusters $\{B, E\}$, $\{A, C\}$ and $\{D, F\}$ unchanged and proceeds with the next highest pairwise correlation, which is given by 0.4, the correlation between C and D, marked in green. Since all pairwise correlations are greater or equal to 0.2, the cluster $\{A, C, D, F\}$ is formed. The algorithm stops here, because the minimum number of clusters is reached.

Figure B.4: Cluster Algorithm
This figure is supposed to illustrate the cluster algorithm, using an example with six anomaly signals.



Appendix C

Option Trading-Implied Prevalence of Asset Pricing Anomalies

This appendix presents the main figures and tables associated with Chapter 4. Section C.1 contains the figures, while Section C.2 reports the corresponding tables. In addition, Section C.3 provides robustness analyses and outlines the sign-restricted structural vector autoregression (SVAR) framework employed to identify option demand shocks originating from end users and market makers.

C.1 Figures

Figure C.1: OTP and Unconditional Anomaly Returns
We plot an anomaly's OTP against its unconditional effect size R^{LS}. The plot illustrates the cluster abbreviations of the single anomaly signal. OTP is depicted on the y-axis while R^{LS} is depicted on the x-axis. The sample we consider consists only of optionable stocks. The sample covers the period from February 1996 to July 2021.

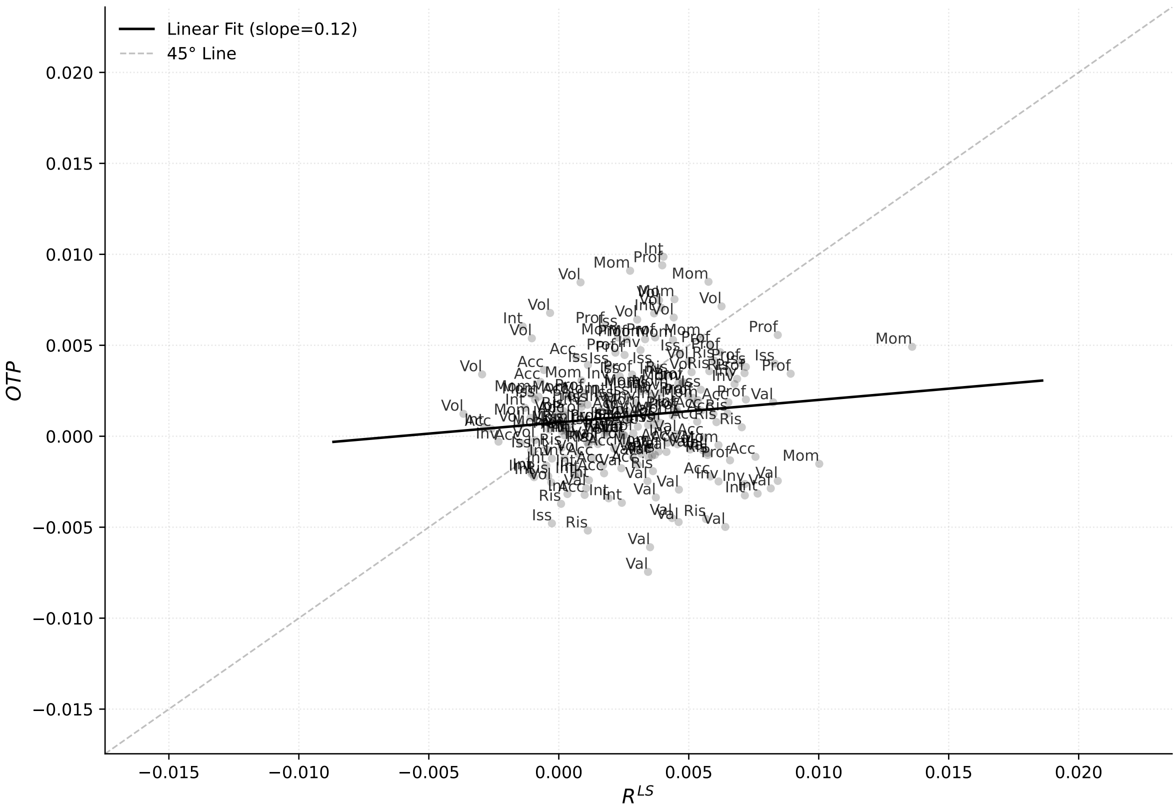


Figure C.2: OTP and Alphas

We plot an anomaly's unconditional alpha against its OTP. We consider alphas in relation to the $CAPM$ and $FF3$-factor model. The sample we consider consists only of optionable stocks. The sample covers the period from February 1996 to July 2021.

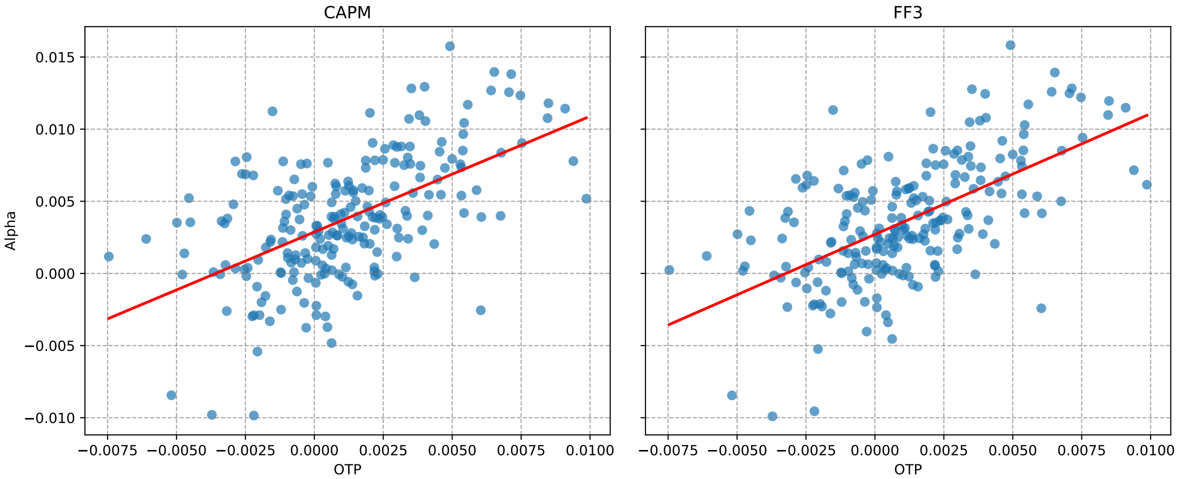


Figure C.3: OTP in Relation to Other Mispricing Measures

We compare OTP to the mispricing measures of Bali et al. (2023) (BBW), Chen et al. (2023) (CLZ), and Frey (2023) ($Frey$). We manually match their respective anomalies to the anomalies used in our analyses. We create a dummy variable indicating whether the respective authors classify the anomaly as mispricing-based or not. We fit a logit model which indicates the probability of an anomaly to be classified as mispricing-based by the respective author.

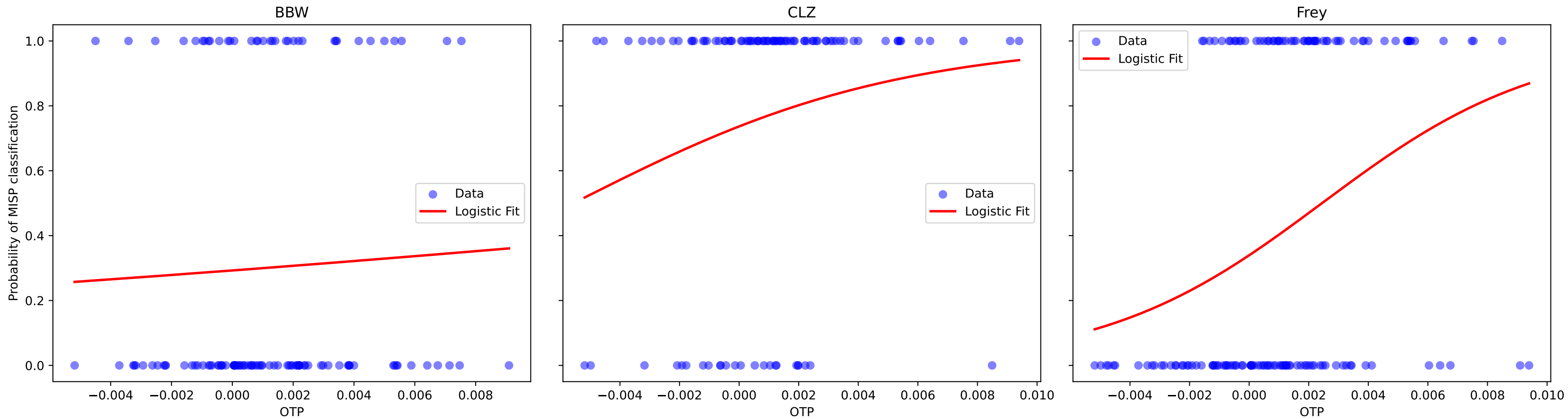
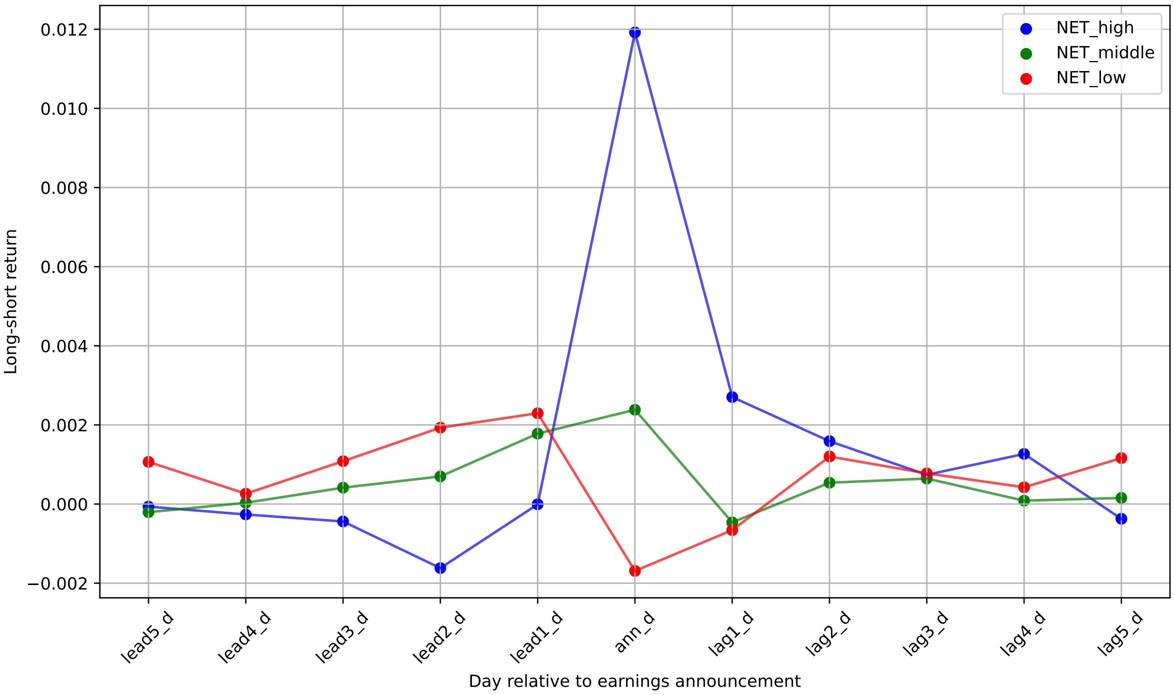


Figure C.4: OTP and Earnings Announcement Returns
We split anomalies into high, middle and low OTP buckets. Following Engelberg et al. (2018), for each stock-month, we then construct $NET_{i,t}^{high}$, $NET_{i,t}^{middle}$ and $NET_{i,t}^{low}$, respectively only considering high, middle or low OTP characteristics. On each day, we sort firms in decile portfolios based on $NET_{i,t}^{high}$, $NET_{i,t}^{middle}$ and $NET_{i,t}^{low}$ and compute daily, pooled long-short returns for the five days leading up to an earnings announcement day, the earnings announcement day itself and the five days after an earnings announcement day. The sample we consider consists only of optionable stocks. The sample covers the period from February 1996 to July 2021.



C.2 Tables

Table C.1: Simulated Portfolio Sorts Conditional on OTV
We evaluate our theoretical framework in a simulation exercise. We consider 2000 stocks in the cross-section with an average risk-premium 1% per month. The remaining parameters are described in Sections 4.2.3 and 4.2.4. Panel A shows results when assuming that option trading volume is proportional to return variance. Panel B shows results when assuming that option trading volume is proportional to the absolute difference between prices and noisy signals. We draw 30,000 panels of returns and characteristics and split them into 100 chunks of 300 observations. We perform dependent double sorts of the 2,000 stocks into 5 × 5 portfolios. We first sort on *OTV* and then, within each *OTV*-quintile, on the simulated characteristic. $\zeta_j = 0$ implies that characteristic C_j is cross-sectionally correlated with the risk premium component in expected returns. $\zeta_j = 1$ implies that characteristic C_j is cross-sectionally correlated with the mispricing component in expected returns.

Panel A: Investors use options for hedging										
			$\zeta_j = 0$					$\zeta_j = 1$		
	low OTV				high OTV	low OTV				high OTV
Low C_j	0.93	0.85	0.71	0.41	-0.52	0.33	0.33	0.32	0.32	0.33
	0.99	0.95	0.90	0.75	0.13	0.71	0.71	0.71	0.72	0.71
	1.02	1.02	1.03	1.02	1.01	0.95	0.95	0.95	0.94	0.95
	1.05	1.09	1.15	1.29	1.90	1.18	1.19	1.19	1.19	1.18
High C_j	1.11	1.20	1.33	1.62	2.56	1.57	1.56	1.56	1.56	1.58
H-L	0.17	0.34	0.62	1.21	3.08	1.24	1.24	1.24	1.23	1.25

Panel B: Investors use options for speculation										
			$\zeta_j = 0$					$\zeta_j = 1$		
	low OTV				high OTV	low OTV				high OTV
Low C_j	0.37	0.37	0.37	0.37	0.37	0.68	0.64	0.55	0.36	-0.18
	0.76	0.76	0.76	0.76	0.76	0.89	0.87	0.83	0.76	0.48
	1.00	1.00	1.00	0.99	1.00	1.01	1.01	1.01	1.01	1.01
	1.24	1.24	1.24	1.24	1.23	1.15	1.16	1.20	1.28	1.55
High C_j	1.62	1.62	1.62	1.62	1.62	1.35	1.39	1.48	1.67	2.21
H-L	1.24	1.25	1.25	1.25	1.24	0.67	0.75	0.94	1.30	2.39

Table C.2: OTP for Individual Signals

The table shows unconditional anomaly returns (in the column labeled R^{LS}), computed from single quintile sorts on the anomaly signals. $R^{LS}_{Q5(O/S)}$ are quintile portfolio anomaly returns within the group of stocks with the highest 20% of option-to-stock trading volume, as in Roll et al. (2010). OTP is the difference between $R^{LS}_{Q5(O/S)}$ and R^{LS}. Returns are displayed in percentage points. T-statistics are calculated using Newey and West (1987) standard errors. The sample consists only of optionable stocks and covers the period from February 1996 to July 2021.

Signal	**Description**	**Authors**	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
		Volatility						
activism2	Active shareholders	Cremers and Nair 2005	0.5	1.36	0.91	1.12	0.41	0.56
betasquared	CAPM beta squred	Fama and MacBeth 1973	-0.1	-0.19	0.43	0.88	0.54	3.11
failureprobability	Failure probability	Campbell, Hilscher and Szilagyi 2008	0.08	0.15	0.93	1.89	0.85	3.79
failureprobabilityjune	Failure probability	Campbell, Hilscher and Szilagyi 2008	-0.03	-0.07	0.64	1.39	0.68	3.55
fr	Pension Funding Status	Franzoni and Marin 2006	-0.37	-1.74	-0.24	-1	0.12	0.65
frbook	Pension Funding Status	Franzoni and Marin 2006	-0.15	-1.26	-0.08	-0.53	0.06	0.48
idiovol3f	Idiosyncratic risk (3 factor)	Ang et al. 2006	0.39	0.75	1.13	2.57	0.75	3.65
idiovolaht	Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley 2003	0.3	0.51	0.94	1.89	0.64	3.06
idiovolcapm	Idiosyncratic risk (CAPM)	Ang et al. 2006	0.39	0.77	1.1	2.46	0.71	3.54
idiovolqf	Idiosyncratic risk (q factor)	Ang et al. 2006	0.63	1.24	1.34	3.31	0.71	3.46
maxret	Maximum return over month	Bali, Cakici, and Whitelaw 2011	0.51	1.11	0.86	2	0.35	2.09
pricedelaytstat	Price delay SE adjusted	Hou and Moskowitz 2005	-0.01	-0.05	0.12	0.64	0.13	1.18
realestate	Real estate holdings	Tuzel 2010	0.27	2.25	0.37	1.74	0.1	0.52
realizedvol	Realized (Total) Volatility	Ang et al. 2006	0.44	0.84	1.09	2.25	0.65	3.5
returnskew	Return skewness	Bali, Engle and Murray 2015	0.15	1.15	0.11	0.64	-0.04	-0.32
returnskew3f	Idiosyncratic skewness (3F model)	Bali, Engle and Murray 2015	-0.09	-0.88	-0.11	-0.82	-0.02	-0.17
returnskewcapm	Idiosyncratic skewness (CAPM)	Bali, Engle and Murray 2015	0.08	0.72	-0.02	-0.15	-0.1	-0.83
returnskewqf	Idiosyncratic skewness (Q model)	Bali, Engle and Murray 2015	-0.03	-0.27	-0.28	-1.78	-0.25	-2.19
varcf	Cash-flow to price variance	Haugen and Baker 1996	-0.3	-0.74	0.05	0.13	0.34	1.69
		Momentum						
announcementreturn	Earnings announcement return	Chan, Jegadeesh and Lakonishok 1996	0.44	3.27	0.55	2.75	0.11	0.75
betavix	Systematic volatility	Ang et al. 2006	0.35	1.91	0.29	1.07	-0.06	-0.38
changeroa	Change in Return on assets	Balakrishnan, Bartov and Faurel 2010	-0.11	-0.56	0.12	0.66	0.23	1.43
changeroe	Change in Return on equity	Balakrishnan, Bartov and Faurel 2010	-0.08	-0.42	0.14	0.65	0.22	1.34
chtax	Change in Taxes	Thomas and Zhang 2011	-0.04	-0.24	-0	-0	0.04	0.3
coskewacx	Coskewness using daily returns	Ang, Chen and Xing 2006	0.54	2.25	0.73	2.85	0.2	1.48
customermomentum	Customer momentum	Cohen and Frazzini 2008	0.42	1.81	0.68	1.78	0.26	0.76
delbreadth	Breadth of ownership	Chen, Hong and Stein 2002	0.46	1.99	0.75	2.31	0.29	1.92
earningsforecastdisparity	Long-vs-short EPS forecasts	Da and Warachka 2011	0.04	0.18	0.27	1.05	0.23	1.49
earningsstreak	Earnings surprise streak	Loh and Warachka 2012	0.31	2.25	0.58	2.87	0.26	1.69

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Signal	Description	Authors	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
earningssurprise	Earnings Surprise	Foster, Olsen and Shevlin 1984	-0.11	-0.91	-0.01	-0.04	0.1	0.77
firmagemom	Firm Age - Momentum	Zhang 2006	1.36	3.45	1.85	3.24	0.49	1.28
high52	52 week high	George and Hwang 2004	0.27	0.52	1.18	2.68	0.91	4.1
indretbig	Industry return of big firms	Hou 2007	1	3.03	0.85	2.15	-0.15	-0.43
iomom_cust	Customers momentum	Menzly and Ozbas 2010	0.32	1.37	0.56	2.35	0.25	1.57
iomom_supp	Suppliers momentum	Menzly and Ozbas 2010	0.31	1.58	0.47	1.96	0.16	1.01
mom12m	Momentum (12 month)	Jegadeesh and Titman 1993	0.45	0.93	1.2	2.8	0.75	2.75
mom12moffseason	Momentum without the seasonal part	Heston and Sadka 2008	0.44	1.06	0.97	2.31	0.53	2.29
mom6m	Momentum (6 month)	Jegadeesh and Titman 1993	0.55	1.44	1.09	3	0.54	2.55
mom6mjunk	Junk Stock Momentum	Avramov et al 2007	0.58	1.27	1.43	3.09	0.85	2.84
numearnincrease	Earnings streak length	Loh and Warachka 2012	0.15	1.34	0.37	2.87	0.22	2.78
residualmomentum	Momentum based on FF3 residuals	Blitz, Huij and Martens 2011	0.33	1.24	0.87	2.79	0.53	3.1
residualmomentum6m	6 month residual momentum	Blitz, Huij and Martens 2011	0.23	1.06	0.77	3.21	0.54	3.74
retconglomerate	Conglomerate return	Cohen and Lou 2012	0.61	2.5	0.57	2.07	-0.05	-0.32
rev6	Earnings forecast revisions	Chan, Jegadeesh and Lakonishok 1996	0.09	0.41	0.39	1.49	0.31	1.69
revenuesurprise	Revenue Surprise	Jegadeesh and Livnat 2006	0.04	0.25	0.1	0.56	0.06	0.46
		Profitability						
analystvalue	Analyst Value	Frankel and Lee 1998	0.16	0.41	0.23	0.51	0.07	0.36
cashdebt	CF to debt	Ou and Penman 1989	0.22	0.81	0.68	2.37	0.46	2.59
cboperprof	Cash-based operating profitability	Ball et al. 2016	0.84	2.94	1.4	4.3	0.56	3.08
cboperproflagat	Cash-based oper prof lagged assets	Ball et al. 2016	0.58	2.49	1.08	3.85	0.5	2.68
cboperproflagat_q	Cash-based oper prof lagged assets qtrly	Ball et al. 2016	0.62	2.51	1.08	3.57	0.46	2.52
compequiss	Composite equity issuance	Daniel and Titman 2006	0.66	2.91	0.53	2.05	-0.13	-0.63
earningsconsistency	Earnings consistency	Alwathainani 2009	0.09	0.51	0.2	0.94	0.12	0.63
etr	Effective Tax Rate	Abarbanell and Bushee 1998	0.01	0.17	0.04	0.23	0.03	0.18
feps	Analyst earnings per share	Cen, Wei, and Zhang 2006	0.37	0.75	0.91	2	0.54	2.57
forecastdispersion	EPS Forecast Dispersion	Diether, Malloy and Scherbina 2002	0.24	0.73	0.22	0.66	-0.03	-0.16
gp	gross profits / total assets	Novy-Marx 2013	0.89	3.8	1.24	4.52	0.34	2.24
gplag	gross profits / total assets	Novy-Marx 2013	0.46	2.68	0.59	2.74	0.13	0.88
gplag_q	gross profits / total assets	Novy-Marx 2013	0.71	3.62	1.06	4.61	0.35	2.27
momseason	Return seasonality years 2 to 5	Heston and Sadka 2008	0.29	1.74	0.3	1.63	0.02	0.1
nanalyst	Number of analysts	Elgers, Lo and Pfeiffer 2001	0.18	0.78	0.78	3.12	0.61	3.99
operprof	operating profits / book equity	Fama and French 2006	0.52	1.48	0.73	2.21	0.21	1.24
operproflag	operating profits / book equity	Fama and French 2006	0.1	0.37	0.33	1.41	0.24	1.32
operproflag_q	operating profits / book equity	Fama and French 2006	0.48	1.36	0.78	2.31	0.3	2.04
operprofrd	Operating profitability R&D adjusted	Ball et al. 2016	0.72	2.14	0.92	2.64	0.2	1.02
operprofrdlagat	Oper prof R&D adj lagged assets	Ball et al. 2016	0.45	2.13	0.59	2.1	0.14	0.87
operprofrdlagat_q	Oper prof R&D adj lagged assets (qtrly)	Ball et al. 2016	0.7	2.12	1.1	3.21	0.4	1.96
pm_q	Profit Margin	Soliman 2008	0.28	0.72	0.62	1.74	0.34	1.78

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Signal	Description	Authors	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
retnoa	Return on Net Operating Assets	Soliman 2008	0.09	0.6	0.27	1.36	0.18	1.19
retnoa_q	Return on Net Operating Assets	Soliman 2008	0.26	0.89	0.34	1.2	0.08	0.4
roaq	Return on assets (qtrly)	Balakrishnan, Bartov and Faurel 2010	0.26	0.71	0.79	2.37	0.53	2.47
roic	Return on invested capital	Brown and Rowe 2007	0.25	0.75	0.7	2.33	0.45	2.41
sfe	Earnings Forecast to price	Elgers, Lo and Pfeiffer 2001	0.4	0.85	1.34	2.4	0.94	2.23
tax	Taxable income to income	Lev and Nissim 2004	0.5	2.03	0.72	2.97	0.22	1.41
		Issuance						
analystrevision	EPS forecast revision	Hawkins, Chamberlin, Daniel 1984	0.13	0.99	0.18	0.92	0.05	0.34
aop	Analyst Optimism	Frankel and Lee 1998	0.11	0.73	0.5	2.73	0.39	2.91
compositedebtissuance	Composite debt issuance	Lyandres, Sun and Zhang 2008	0.2	2.18	0.28	1.52	0.08	0.57
ep	Earnings-to-Price Ratio	Basu 1977	0.21	0.81	0.29	0.9	0.08	0.56
equityduration	Equity Duration	Dechow, Sloan and Soliman 2004	0.21	0.65	0.41	1.09	0.2	0.97
fgr5yrlag	Long-term EPS forecast	La Porta 1996	0.11	0.32	0.28	0.69	0.17	1.07
intrinsicvalue	Intrinsic or historical value	Frankel and Lee 1998	0.23	0.72	0.81	2.32	0.59	3.05
meanrankrevgrowth	Revenue Growth Rank	Lakonishok, Shleifer, Vishny 1994	-0.11	-0.76	-0.18	-0.96	-0.08	-0.5
momoffseason06yrplus	Off season reversal years 6 to 10	Heston and Sadka 2008	0.37	2.43	0.43	2.03	0.06	0.46
netequityfinance	Net equity financing	Bradshaw, Richardson, Sloan 2006	0.34	1.17	0.59	1.89	0.25	2.1
netpayoutyield	Net Payout Yield	Boudoukh et al. 2007	0.47	1.52	0.92	2.6	0.45	2.99
orderbacklogchg	Change in order backlog	Baik and Ahn 2007	-0.03	-0.12	-0.51	-1.44	-0.48	-1.59
payoutyield	Payout Yield	Boudoukh et al. 2007	0.27	1.41	0.48	1.77	0.21	1.22
payoutyield_q	Payout Yield quarterly	Boudoukh et al. 2007	0.23	1.49	0.56	2.23	0.33	2.01
pm	Profit Margin	Soliman 2008	0.19	0.52	0.58	1.66	0.38	1.76
predictedfe	Predicted Analyst forecast error	Frankel and Lee 1998	-0.09	-0.36	0.11	0.35	0.2	1.14
roe	net income / book equity	Haugen and Baker 1996	0.36	1.24	0.74	2.69	0.38	2.06
shareiss1y	Share issuance (1 year)	Pontiff and Woodgate 2008	0.72	2.69	1.1	3.73	0.38	3.04
shareiss5y	Share issuance (5 year)	Daniel and Titman 2006	0.55	2.47	0.8	3.37	0.26	1.95
xfin	Net external financing	Bradshaw, Richardson, Sloan 2006	0.83	2.52	1.23	3.32	0.4	2.63
		Investment						
accrualquality	Accrual Quality	Francis, LaFond, Olsson, Schipper 2005	-0.11	-0.4	-0.31	-1.17	-0.21	-1.19
ageipo	IPO and age	Ritter 1991	0.4	0.84	0.72	1.04	0.33	0.74
cf	Cash flow to market	Lakonishok, Shleifer, Vishny 1994	0.48	1.19	0.77	1.76	0.29	1.49
cfp	Operating Cash flows to price	Desai, Rajgopal, Venkatachalam 2004	0.69	1.94	1	2.7	0.32	1.69
cfpq	Operating Cash flows to price quarterly	Desai, Rajgopal, Venkatachalam 2004	0.68	2.3	0.96	2.84	0.29	1.69
cfq	Cash flow to market quarterly	Lakonishok, Shleifer, Vishny 1994	0.31	0.73	0.79	1.77	0.47	2.12
chinv	Inventory Growth	Thomas and Zhang 2002	0.3	2.63	0.48	2.44	0.18	1.33
chinvia	Change in capital inv (ind adj)	Abarbanell and Bushee 1998	0.27	2.21	0.4	2.46	0.13	1
delayacct	Accounting component of price delay	Callen, Khan and Lu 2013	-0.23	-1.22	-0.26	-1.08	-0.03	-0.14

Continued on next page

Signal	**Description**	**Authors**	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
delfinl	Change in financial liabilities	Richardson et al. 2005	0.27	2.64	0.37	2.24	0.1	0.83
delnetfin	Change in net financial assets	Richardson et al. 2005	0.11	0.97	0.08	0.46	-0.03	-0.27
entmult	Enterprise Multiple	Loughran and Wellman 2011	0.72	1.96	0.45	1.05	-0.26	-1.48
entmult_q	Enterprise Multiple quarterly	Loughran and Wellman 2011	0.61	1.83	0.37	0.93	-0.25	-1.61
epq	Earnings-to-Price Ratio	Basu 1977	0.2	0.77	0.5	1.59	0.3	2.16
exclexp	Excluded Expenses	Doyle, Lundholm and Soliman 2003	0.09	0.58	0.25	1.48	0.16	1.11
grcapx	Change in capex (two years)	Anderson and Garcia-Feijoo 2006	0.39	2.39	0.58	2.46	0.19	1.36
grcapx1y	Investment growth (1 year)	Anderson and Garcia-Feijoo 2006	0.02	0.17	0.03	0.15	0.01	0.04
grcapx3y	Change in capex (three years)	Anderson and Garcia-Feijoo 2006	0.39	2.48	0.63	2.66	0.24	1.66
grgmtogrsales	Gross margin growth to sales growth	Abarbanell and Bushee 1998	0.19	1.78	0.36	2.08	0.18	1.34
grsaletogrinv	Sales growth over inventory growth	Abarbanell and Bushee 1998	-0.01	-0.12	0.08	0.45	0.09	0.7
investment	Investment to revenue	Titman, Wei and Xie 2004	0.19	1.43	0.22	0.99	0.03	0.21
investppeinv	change in ppe and inv/assets	Lyandres, Sun and Zhang 2008	0.43	2.8	0.42	1.9	-0.01	-0.09
invgrowth	Inventory Growth	Belo and Lin 2012	0.36	2.42	0.58	2.49	0.22	1.33
momoffseason16yrplus	Off season reversal years 16 to 20	Heston and Sadka 2008	-0.03	-0.26	-0.15	-0.64	-0.12	-0.59
netdebtfinance	Net debt financing	Bradshaw, Richardson, Sloan 2006	0.34	3.52	0.41	2.38	0.06	0.47
pchgm_pchsale	Change in gross margin vs sales	Abarbanell and Bushee 1998	0.12	1.13	0.19	1.19	0.07	0.57
pchsaleinv	Change in sales to inventory	Ou and Penman 1989	0.03	0.28	0.07	0.41	0.04	0.31
		Accruals						
abnormalaccruals	Abnormal Accruals	Xie 2001	0.17	1.68	-0.03	-0.19	-0.2	-1.38
abnormalaccrualspercent	Percent Abnormal Accruals	Hafzalla, Lundholm, Van Winkle 2011	0.23	3.5	0.37	2.47	0.14	0.99
accruals	Accruals	Sloan 1996	0.13	0.88	0.01	0.07	-0.12	-0.67
assetgrowth	Asset growth	Cooper, Gulen and Schill 2008	0.65	3.47	0.84	3.34	0.19	1.23
assetgrowth_q	Asset growth quarterly	Cooper, Gulen and Schill 2008	0.76	2.82	0.64	2.03	-0.11	-0.56
changeinrecommendation	Change in recommendation	Jegadeesh et al. 2004	0.36	4.62	0.25	1.5	-0.11	-0.77
chassetturnover	Change in Asset Turnover	Soliman 2008	0.02	0.25	0.14	0.9	0.11	0.96
cheq	Growth in book equity	Lockwood and Prombutr 2010	0.59	3.31	0.72	2.91	0.12	0.76
chncoa	Change in Noncurrent Operating Assets	Soliman 2008	0.56	3.54	0.55	2.75	-0.01	-0.05
chncol	Change in Noncurrent Operating Liab	Soliman 2008	0.42	2.87	0.38	1.66	-0.04	-0.22
chnncoa	Change in Net Noncurrent Op Assets	Soliman 2008	0.17	1.81	0.01	0.05	-0.16	-0.98
chnwc	Change in Net Working Capital	Soliman 2008	0.03	0.41	0.06	0.43	0.02	0.19
chpm	Change in Profit Margin	Soliman 2008	-0.06	-0.45	0.31	1.7	0.36	2.42
coskewness	Coskewness	Harvey and Siddique 2000	0.3	1.79	0.36	1.79	0.05	0.46
delcoa	Change in current operating assets	Richardson et al. 2005	0.23	1.66	0.3	1.5	0.07	0.51
delcol	Change in current operating liabilities	Richardson et al. 2005	0.23	1.44	0.24	1.05	0.01	0.05
delequ	Change in equity to assets	Richardson et al. 2005	0.55	2.93	0.69	2.99	0.14	0.94
dnoa	change in net operating assets	Hirshleifer, Hou, Teoh, Zhang 2004	0.53	3.27	0.61	2.74	0.08	0.56
gradexp	Growth in advertising expenses	Lou 2014	0.58	3.16	0.36	1.38	-0.22	-0.94
grsaletogroverhead	Sales growth over overhead growth	Abarbanell and Bushee 1998	-0.26	-2.22	-0.22	-1.31	0.04	0.3

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Signal	Description	Authors	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
grsaletogrreceivables	Change in sales vs change in receiv	Abarbanell and Bushee 1998	0.1	1.05	-0.22	-1.54	-0.32	-2.41
hire	Employment growth	Bazdresch, Belo and Lin 2014	0.46	2.42	0.41	1.72	-0.04	-0.33
intmom	Intermediate Momentum	Novy-Marx 2012	-0.07	-0.18	0.23	0.59	0.3	1.45
laborforceefficiency	Laborforce efficiency	Abarbanell and Bushee 1998	-0.15	-1.7	-0.18	-0.92	-0.04	-0.22
momseasonshort	Return seasonality last year	Heston and Sadka 2008	0.04	0.15	0.26	0.88	0.22	1.35
pctacc	Percent Operating Accruals	Hafzalla, Lundholm, Van Winkle 2011	0.37	2.88	0.47	2.67	0.1	0.62
pcttotacc	Percent Total Accruals	Hafzalla, Lundholm, Van Winkle 2011	0.21	1.88	0.15	0.97	-0.07	-0.53
saleinv	Sales to inventory	Ou and Penman 1989	0.07	0.54	0.5	3.19	0.43	3.26
totalaccruals	Total accruals	Richardson et al. 2005	0.3	2.02	0.15	0.8	-0.16	-0.98
		Risk						
adexp	Advertising Expense	Chan, Lakonishok and Sougiannis 2001	0.57	1.39	0.11	0.22	-0.45	-1.51
assetturnover	Asset Turnover	Soliman 2008	0.6	3.23	1.01	4.75	0.42	3.44
assetturnover_q	Asset Turnover	Soliman 2008	0.58	3.26	0.94	4.59	0.36	2.74
beta	CAPM beta	Fama and MacBeth 1973	0.11	0.21	-0.41	-0.82	-0.52	-3.02
betafp	Frazzini-Pedersen Beta	Frazzini and Pedersen 2014	0.01	0.02	-0.36	-0.75	-0.37	-2.02
betaliquidityps	Pastor-Stambaugh liquidity beta	Pastor and Stambaugh 2003	0.01	0.07	-0.05	-0.23	-0.06	-0.43
betatailrisk	Tail risk beta	Kelly and Jiang 2014	0.36	1.12	0.17	0.52	-0.19	-0.94
brandcapital	Brand capital to assets	Belo, Lin and Vitorino 2014	0.57	2.57	0.47	1.47	-0.1	-0.3
capturnover	Capital turnover	Haugen and Baker 1996	0.42	2.41	0.76	3.23	0.34	2.26
capturnover_q	Capital turnover (quarterly)	Haugen and Baker 1996	0.66	3.53	1	4.58	0.35	2.43
dellti	Change in long-term investment	Richardson et al. 2005	0.11	1.39	0.07	0.53	-0.05	-0.4
delsti	Change in short-term investment	Richardson et al. 2005	0.18	1.96	0.2	1.13	0.02	0.15
downsidebeta	Downside beta	Ang, Chen and Xing 2006	-0.04	-0.08	-0.26	-0.5	-0.22	-1.23
forecastdispersionlt	Long-term forecast dispersion	Anderson, Ghysels, and Juergens 2005	0.02	0.06	0.08	0.23	0.06	0.43
grltnoa	Growth in long term operating assets	Fairfield, Whisenant and Yohn 2003	0.02	0.16	0.16	0.84	0.14	0.84
opleverage	Operating leverage	Novy-Marx 2011	0.65	3.49	0.77	3.95	0.13	0.93
opleverage_q	Operating leverage (qtrly)	Novy-Marx 2011	0.61	3.15	0.68	3.54	0.08	0.57
orgcap	Organizational capital	Eisfeldt and Papanikolaou 2013	0.37	2.86	0.27	1.11	-0.1	-0.56
orgcapnoadj	Org cap w/o industry adjustment	Eisfeldt and Papanikolaou 2013	0.7	2.71	0.75	2.21	0.05	0.28
		Intangibles						
assetliquiditybook	Asset liquidity over book assets	Ortiz-Molina and Phillips 2014	0.07	0.21	0.08	0.21	0.01	0.06
assetliquiditybookquart	Asset liquidity over book (qtrly)	Ortiz-Molina and Phillips 2014	0.04	0.12	0.05	0.15	0.01	0.05
bookleverage	Book leverage (annual)	Fama and French 1992	-0.09	-0.29	-0.32	-0.92	-0.22	-1.82
bookleveragequarterly	Book leverage (quarterly)	Fama and French 1992	-0.1	-0.32	-0.3	-0.91	-0.2	-1.76
bpebm	Leverage component of BM	Penman, Richardson and Tuna 2007	-0.29	-1.48	-0.24	-1.3	0.05	0.31
cash	Cash to assets	Palazzo 2012	0.25	0.62	0.26	0.62	0.01	0.03
depr	Depreciation to PPE	Holthausen and Larcker 1992	0.34	1.32	0.27	0.97	-0.07	-0.48

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Signal	Description	Authors	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
ebm	Enterprise component of BM	Penman, Richardson and Tuna 2007	0.19	1.01	-0.15	-0.66	-0.34	-2.2
ebm_q	Enterprise component of BM	Penman, Richardson and Tuna 2007	0.24	1.28	-0.12	-0.57	-0.37	-2.29
herf	Industry concentration (sales)	Hou and Robinson 2006	0.02	0.07	-0.1	-0.29	-0.12	-0.78
herfasset	Industry concentration (assets)	Hou and Robinson 2006	0.06	0.23	-0.11	-0.39	-0.18	-1.24
herfbe	Industry concentration (equity)	Hou and Robinson 2006	0.08	0.31	-0.13	-0.45	-0.21	-1.51
kz	Kaplan Zingales index	Lamont, Polk and Saa-Requejo 2001	-0.05	-0.19	-0.12	-0.47	-0.07	-0.48
kz_q	Kaplan Zingales index quarterly	Lamont, Polk and Saa-Requejo 2001	-0.13	-0.44	0.03	0.09	0.16	1.03
netdebtprice	Net debt to price	Penman, Richardson and Tuna 2007	0.37	1.02	1.04	2.68	0.68	2.54
netdebtprice_q	Net debt to price	Penman, Richardson and Tuna 2007	0.4	1.06	1.39	3.18	0.99	3.48
noa	Net Operating Assets	Hirshleifer et al. 2004	0.45	2.42	0.6	2.68	0.15	1.04
orderbacklog	Order backlog	Rajgopal, Shevlin, Venkatachalam 2003	-0.14	-0.7	0.46	1.39	0.6	2.22
pchdepr	Change in depreciation to PPE	Holthausen and Larcker 1992	0.12	1.06	-0.13	-0.68	-0.24	-1.46
rd	R&D over market cap	Chan, Lakonishok and Sougiannis 2001	0.72	1.88	0.39	1.42	-0.33	-1.39
rd_q	R&D over market cap quarterly	Chan, Lakonishok and Sougiannis 2001	0.76	1.87	0.45	1.48	-0.32	-1.17
rd_sale	R&D to sales	Chan, Lakonishok and Sougiannis 2001	0.06	0.13	-0.16	-0.36	-0.22	-1.01
rd_sale_q	R&D to sales	Chan, Lakonishok and Sougiannis 2001	-0.05	-0.11	-0.21	-0.55	-0.16	-0.68
tang	Tangibility	Hahn and Lee 2009	0.03	0.1	-0.28	-0.8	-0.32	-1.75
tang_q	Tangibility quarterly	Hahn and Lee 2009	0.18	0.76	0.4	1.27	0.22	1.22
		Value						
am	Total assets to market	Fama and French 1992	0.44	0.93	-0.01	-0.03	-0.45	-2.33
amq	Total assets to market (quarterly)	Fama and French 1992	0.35	0.78	-0.26	-0.57	-0.61	-3.24
assetliquiditymarket	Asset liquidity over market	Ortiz-Molina and Phillips 2014	0.39	1.43	0.46	1.31	0.07	0.52
assetliquiditymarketquart	Asset liquidity over market (qtrly)	Ortiz-Molina and Phillips 2014	0.24	0.76	0.06	0.17	-0.18	-1.07
bm	Book to market, original (Stattman 1980)	Stattman 1980	0.36	1.28	0.47	1.36	0.11	0.73
bmdec	Book to market using December ME	Fama and French 1992	0.18	0.63	0.18	0.5	0.01	0.04
bmq	Book to market (quarterly)	Rosenberg, Reid, and Lanstein 1985	0.34	0.87	-0.4	-1.03	-0.75	-3.57
cashprod	Cash Productivity	Chandrashekar and Rao 2009	0.11	0.35	-0.18	-0.45	-0.29	-1.86
frontier	Efficient frontier index	Nguyen and Swanson 2009	0.64	1.51	0.14	0.41	-0.5	-2.19
intanbm	Intangible return using BM	Daniel and Titman 2006	0.46	1.29	-0.01	-0.03	-0.47	-2.61
intancfp	Intangible return using CFtoP	Daniel and Titman 2006	0.52	1.75	0.47	1.44	-0.05	-0.31
intanep	Intangible return using EP	Daniel and Titman 2006	0.41	1.64	0.33	1.09	-0.09	-0.52
intansp	Intangible return using Sale2P	Daniel and Titman 2006	0.34	0.91	0.09	0.24	-0.25	-1.07
leverage	Market leverage	Bhandari 1988	0.46	1	0.17	0.33	-0.29	-1.67
leverage_q	Market leverage quarterly	Bhandari 1988	0.37	0.83	0.04	0.08	-0.34	-1.91
lrreversal	Long-run reversal	De Bondt and Thaler 1985	0.45	1.53	0.46	1.37	0.01	0.05
momoffseason	Off season long-term reversal	Heston and Sadka 2008	0.5	1.72	0.43	1.24	-0.07	-0.42
momoffseason11yrplus	Off season reversal years 11 to 15	Heston and Sadka 2008	0.25	2.01	0.25	1.06	0.01	0.04
momseason06yrplus	Return seasonality years 6 to 10	Heston and Sadka 2008	0.57	4.22	0.48	2.56	-0.09	-0.67
momseason11yrplus	Return seasonality years 11 to 15	Heston and Sadka 2008	0.28	2.54	0.17	0.95	-0.11	-0.82

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Signal	**Description**	**Authors**	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
momseason16yrplus	Return seasonality years 16 to 20	Heston and Sadka 2008	0.55	4.5	0.48	1.86	-0.08	-0.41
mrreversal	Medium-run reversal	De Bondt and Thaler 1985	0.35	1.26	0.23	0.71	-0.12	-0.63
rds	Real dirty surplus	Landsman et al. 2011	0.14	0.97	0.11	0.68	-0.02	-0.22
sp	Sales-to-price	Barbee, Mukherji and Raines 1996	0.84	1.77	0.6	1.22	-0.25	-1.24
sp_q	Sales-to-price quarterly	Barbee, Mukherji and Raines 1996	0.82	1.73	0.53	1.08	-0.29	-1.58
trendfactor	Trend Factor	Han, Zhou, Zhu 2016	0.82	3.46	1.01	2.96	0.19	1.1
zscore	Altman Z-Score	Dichev 1998	0.32	0.74	0.22	0.5	-0.1	-0.44
zscore_q	Altman Z-Score quarterly	Dichev 1998	0.38	0.82	0.3	0.65	-0.08	-0.33

Table C.3: OTP for Anomaly Clusters
The table shows unconditional anomaly returns (in the column labeled R^{LS}), computed from single quintile sorts on the anomaly signals. $R^{LS}_{Q5(O/S)}$ are quintile portfolio anomaly returns within the group of stocks with the highest 20% of option-to-stock trading volume, as in Roll et al. (2010). OTP is the difference between $R^{LS}_{Q5(O/S)}$ and R^{LS}. Returns are displayed in percentage points. T-statistics are calculated using Newey and West (1987) standard errors. We average returns and OTP across all anomalies in our sample ("Aggregate"), and across anomalies in several clusters. The sample consists only of optionable stocks and covers the period from February 1996 to July 2021.

Cluster	R^{LS}	t	$R^{LS}_{Q5(O/S)}$	t	OTP	t
Aggregate	0.29	4.18	0.40	5.03	0.11	3.84
Volatility	0.11	0.35	0.45	1.72	0.35	3.03
Momentum	0.34	2.02	0.65	3.68	0.30	3.37
Profitability	0.40	1.85	0.70	3.27	0.29	2.73
Issuance	0.27	1.39	0.48	2.33	0.22	2.87
Investment	0.27	2.57	0.37	3.02	0.10	1.92
Accruals	0.26	3.69	0.29	3.61	0.03	0.51
Risk	0.34	2.42	0.34	2.92	-0.01	-0.09
Intangibles	0.14	0.60	0.12	0.57	-0.02	-0.24
Value	0.42	1.63	0.24	0.91	-0.18	-1.67

Table C.4: OTP and Original Author Classification
We match 143 anomalies from Chen et al. (2023) to those used in our analyses. Chen et al. (2023) provide anomaly classifications based on the original author's statements. We calculate long-short returns averaged across the anomalies in the respective classification. We do this unconditionally as well as on high option-to-stock volume (O/S) stocks. The sample we consider consists only of optionable stocks. t-statistics are calculated using Newey and West (1987) standard errors. $*$, $**$, and $***$ indicate significance at the 10%, 5% and 1% level. Returns are displayed in percent. The sample covers the period from February 1996 to July 2021.

	R^{LS}	$R^{LS}_{Q5(O/S)}$	OTP
Panel A: Mispricing anomalies (76)			
R	0.29***	0.43***	0.14***
t	(3.13)	(4.11)	(3.22)
Panel B: Risk anomalies (24)			
R	0.32***	0.32***	0.00
t	(3.64)	(3.27)	(0.06)
Panel C: Agnostic anomalies (43)			
R	0.34***	0.44***	0.09**
t	(3.29)	(3.74)	(2.32)

Table C.5: Option End-User and Market Maker Demand Shocks and OTP
The table reports daily panel regressions of option end-user and market maker demand shocks for call and put options on stock i on lagged anomaly signals split into high, middle, and low OTP buckets. Following Engelberg et al. (2018), we construct $\text{NET}_{i,t}^{\text{high}}$, $\text{NET}_{i,t}^{\text{middle}}$, and $\text{NET}_{i,t}^{\text{low}}$ using only characteristics within the respective OTP tercile. Option end-user and market maker demand shocks are derived from a sign-restricted vector auto regression. t-statistics, reported in parentheses, are based on double-clustered standard errors by firm and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample includes optionable stocks from May 2005 to June 2021.

	Call options		Put options	
	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: End-user demand shocks$_{i,t}$				
$\text{NET}_{i,t-1}^{\text{high}}$	0.05^{***}	0.09^{***}	-0.06^{***}	-0.22^{***}
	(6.13)	(7.15)	(-6.45)	(-17.06)
$\text{NET}_{i,t-1}^{\text{middle}}$	0.00	-0.00	0.02^{*}	0.06^{***}
	(0.02)	(-0.34)	(1.94)	(5.54)
$\text{NET}_{i,t-1}^{\text{low}}$	0.02^{*}	0.03^{*}	0.12^{***}	0.21^{***}
	(1.81)	(1.86)	(10.52)	(12.28)
Panel B: Dependent Variable: Market maker demand shocks$_{i,t}$				
$\text{NET}_{i,t-1}^{\text{high}}$	0.04^{***}	0.06^{***}	-0.04***	-0.24***
	(4.61)	(4.69)	(-5.03)	(-18.97)
$\text{NET}_{i,t-1}^{\text{middle}}$	0.01	0.00	0.00	0.05^{***}
	(0.76)	(0.02)	(0.36)	(4.20)
$\text{NET}_{i,t-1}^{\text{low}}$	0.04^{***}	0.08^{***}	0.09^{***}	0.12^{***}
	(4.15)	(4.79)	(7.78)	(6.67)
Observations	6,962,483	6,962,483	6,891,365	6,891,365
Entity fixed effects	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes

C.3 Further Analyses

This section of the appendix includes additional information on and complementary results to Chapter 4. Subsection C.3.1 provides robustness checks, specifically adjusting for stock trading volume as well as providing results by option type and moneyness. Subsection C.3.2 describes the sign-restricted structural vector autoregression (SVAR) used to identify option demand shocks for end user and market makers.

C.3.1 Further Tables

Table C.6: OTP for Anomaly Clusters - Adjusted for Stock Trading Volume
The table shows unconditional anomaly returns (in the column labeled R^{LS}), computed from single quintile sorts on the anomaly signals. For $R^{LS}_{adj,\,Q5(O/S)}$, we perform a dependent $5x5x5$ sort on stock volume, the option-to-stock volume ratio and the respective anomaly signal. $R^{LS}_{adj,\,Q5(O/S)}$ are quintile portfolio anomaly returns within the group of stocks with the highest 20% option-to-stock trading volume, averaged over all stock volume quintiles. OTP_{adj} is the difference between $R^{LS}_{adj,\,Q5(O/S)}$ and R^{LS}. Returns are displayed in percentage points. T-statistics are calculated using Newey and West (1987) standard errors. We average returns and OTP across all anomalies in our sample ("Aggregate"), and across anomalies in several clusters. The sample consists only of optionable stocks and covers the period from February 1996 to July 2021.

Cluster	R^{LS}	t	$R^{LS}_{adj,\,Q5(O/S)}$	t	OTP_{adj}	t
Aggregate	0.29	4.18	0.4	5.76	0.1	4.15
Momentum	0.34	2.02	0.64	4.28	0.3	3.91
Volatility	0.11	0.35	0.4	1.75	0.3	2.5
Profitability	0.4	1.85	0.68	3.3	0.28	3
Issuance	0.27	1.39	0.49	2.63	0.23	3.14
Investment	0.27	2.57	0.3	2.88	0.04	0.69
Accruals	0.26	3.69	0.29	3.47	0.03	0.44
Intangibles	0.14	0.6	0.15	0.67	0.01	0.1
Risk	0.34	2.42	0.31	3.09	-0.03	-0.41
Value	0.42	1.63	0.29	1.19	-0.14	-1.5

Table C.7: OTP for Anomaly Clusters - Option Type and Long and Short Legs
The table shows unconditional long and short portfolio returns reported in columns labeled R^L (long leg) and R^S (short leg), based on single quintile sorts on the anomaly signals. $R^L_{Q5(O/S)}$ and $R^S_{Q5(O/S)}$ denote the corresponding long and short leg returns within the group of stocks with the highest 20% of option-to-stock trading volume. OTP_L and OTP_S capture the deviation of each leg's return in the high-option-volume group from its unconditional benchmark. We report results for the total option-to-stock (Panel A), call-to-stock (Panel B) and put-to-stock trading volume (Panel C). Returns are displayed in percentage points. T-statistics are calculated using Newey and West (1987) standard errors. We average returns and OTP across all anomalies in our sample ("Aggregate"), and across anomalies in several clusters. The sample consists only of optionable stocks and covers the period from February 1996 to July 2021.

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Panel A: Total volume										
Aggregate	0.88	0.49	-0.39	-3.28	1.17	0.89	-0.28	-2.62	0.11	3.84
Volatility	0.95	0.41	-0.54	-3.62	1.06	0.86	-0.2	-2.09	0.35	3.03
Momentum	0.85	0.36	-0.49	-3.66	1.19	1.01	-0.18	-1.57	0.3	3.37
Profitability	0.78	0.25	-0.53	-3.47	1.19	0.95	-0.24	-2.27	0.29	2.73
Issuance	0.91	0.51	-0.39	-2.96	1.17	1	-0.18	-1.99	0.22	2.87
Investment	0.88	0.52	-0.36	-3.07	1.15	0.89	-0.25	-2.29	0.1	1.92
Accruals	0.87	0.51	-0.36	-2.94	1.13	0.8	-0.33	-2.64	0.03	0.51
Risk	0.83	0.53	-0.31	-2.65	1.18	0.86	-0.31	-2.38	-0.01	-0.09
Intangibles	1.01	0.68	-0.33	-2.86	1.15	0.81	-0.35	-2.78	-0.02	-0.24
Value	0.85	0.62	-0.22	-2.15	1.27	0.87	-0.41	-3.23	-0.18	-1.67
Panel B: Call volume										
Aggregate	0.88	0.55	-0.33	-2.66	1.17	0.96	-0.21	-1.87	0.12	3.79
Volatility	0.95	0.51	-0.44	-2.88	1.06	0.87	-0.19	-1.95	0.26	2.23
Momentum	0.85	0.45	-0.4	-2.96	1.19	1.03	-0.16	-1.25	0.24	2.67
Issuance	0.91	0.55	-0.36	-2.65	1.17	1.04	-0.13	-1.35	0.23	2.9
Profitability	0.78	0.37	-0.41	-2.61	1.19	1	-0.19	-1.58	0.22	1.91
Investment	0.88	0.57	-0.31	-2.55	1.15	0.96	-0.19	-1.55	0.12	2.19
Accruals	0.87	0.56	-0.31	-2.34	1.13	0.87	-0.26	-1.9	0.05	0.88
Intangibles	1.01	0.75	-0.27	-2.12	1.15	0.9	-0.25	-2.02	0.01	0.15
Risk	0.83	0.6	-0.24	-2.01	1.18	0.92	-0.26	-1.87	-0.02	-0.23
Value	0.85	0.61	-0.24	-2.21	1.27	1	-0.27	-2.06	-0.03	-0.24
Panel C: Put volume										
Aggregate	0.88	0.45	-0.43	-4.05	1.17	0.83	-0.34	-3.61	0.09	3.49
Profitability	0.78	0.18	-0.6	-4.38	1.19	0.95	-0.23	-2.52	0.37	3.86
Volatility	0.95	0.39	-0.56	-3.93	1.06	0.83	-0.23	-2.73	0.33	2.77
Momentum	0.85	0.32	-0.53	-4.47	1.19	0.95	-0.24	-2.4	0.29	3.28
Issuance	0.91	0.49	-0.42	-3.56	1.17	0.93	-0.25	-3.26	0.17	2.36
Intangibles	1.01	0.54	-0.47	-4.48	1.15	0.83	-0.32	-2.75	0.15	1.77
Investment	0.88	0.48	-0.4	-3.58	1.15	0.8	-0.35	-3.6	0.04	0.84

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Table C.7 – continued from previous page

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Risk	0.83	0.47	-0.37	-3.74	1.18	0.84	-0.34	-2.78	0.03	0.33
Accruals	0.87	0.49	-0.38	-3.42	1.13	0.74	-0.39	-3.54	-0.01	-0.3
Value	0.85	0.67	-0.18	-1.91	1.27	0.64	-0.63	-5.24	-0.45	-4.1

Table C.8: OTP for Anomaly Clusters - Long and Short Legs by Moneyness
The table shows unconditional long and short portfolio returns reported in columns labeled R^L (long leg) and R^S (short leg), based on single quintile sorts on the anomaly signals. $R^L_{Q5(O/S)}$ and $R^S_{Q5(O/S)}$ denote the corresponding long and short leg returns within the group of stocks with the highest 20% of option-to-stock trading volume. OTP_L and OTP_S capture the deviation of each leg's return in the high-option-volume group from its unconditional benchmark. We report results for total, call and put option type volumes as well as different moneyness categories. Returns are displayed in percentage points. T-statistics are calculated using Newey and West (1987) standard errors. We average returns and OTP across all anomalies in our sample ("Aggregate"), and across anomalies in several clusters. The sample consists only of optionable stocks and covers the period from February 1996 to July 2021.

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Panel A: Total volume - DOTM										
Aggregate	0.88	0.55	-0.33	-3.05	1.17	0.91	-0.26	-2.67	0.08	2.85
Volatility	0.96	0.54	-0.42	-3.17	1.06	0.92	-0.14	-1.61	0.28	2.89
Momentum	0.85	0.41	-0.45	-3.69	1.19	1	-0.19	-1.73	0.26	2.9
Profitability	0.79	0.35	-0.44	-3.48	1.19	0.97	-0.22	-2.02	0.22	2.42
Issuance	0.91	0.55	-0.36	-2.81	1.17	0.98	-0.19	-2.35	0.16	2.27
Intangibles	1.01	0.68	-0.33	-2.98	1.16	0.89	-0.27	-2.25	0.06	0.6
Investment	0.88	0.59	-0.3	-2.56	1.15	0.91	-0.24	-2.45	0.06	0.8
Accruals	0.88	0.56	-0.32	-2.66	1.14	0.8	-0.34	-2.78	-0.02	-0.26
Risk	0.83	0.55	-0.28	-2.57	1.18	0.87	-0.31	-2.59	-0.03	-0.36
Value	0.85	0.71	-0.14	-1.34	1.27	0.89	-0.38	-3.37	-0.24	-2.14
Panel B: Total volume - OTM										
Aggregate	0.88	0.47	-0.42	-3.58	1.17	0.86	-0.31	-3.12	0.1	3.37
Volatility	0.96	0.4	-0.56	-3.82	1.06	0.87	-0.19	-2.26	0.36	3.34
Profitability	0.79	0.26	-0.52	-3.53	1.19	0.94	-0.25	-2.47	0.27	2.77
Momentum	0.85	0.36	-0.49	-3.85	1.19	0.96	-0.23	-2.01	0.26	2.84
Issuance	0.91	0.48	-0.43	-3.23	1.17	0.97	-0.2	-2.41	0.23	2.75
Investment	0.88	0.49	-0.4	-3.31	1.15	0.84	-0.31	-3	0.08	1.3
Accruals	0.88	0.49	-0.39	-3.18	1.14	0.78	-0.35	-2.96	0.04	0.61
Intangibles	1.01	0.62	-0.39	-3.59	1.16	0.78	-0.38	-3.12	0.01	0.1
Risk	0.83	0.49	-0.34	-3.27	1.18	0.79	-0.39	-2.95	-0.05	-0.61
Value	0.85	0.59	-0.26	-2.41	1.27	0.82	-0.45	-3.94	-0.19	-1.72
Panel C: Total volume - ATM										
Aggregate	0.88	0.59	-0.29	-2.5	1.17	0.98	-0.19	-1.82	0.1	3.09
Volatility	0.96	0.55	-0.41	-2.79	1.06	0.92	-0.14	-1.55	0.27	2.46
Momentum	0.85	0.49	-0.36	-2.79	1.19	1.05	-0.14	-1.21	0.22	2.41
Issuance	0.91	0.61	-0.31	-2.35	1.17	1.05	-0.12	-1.34	0.18	2.35
Profitability	0.79	0.44	-0.35	-2.32	1.19	1.01	-0.18	-1.66	0.17	1.54
Intangibles	1.01	0.72	-0.29	-2.52	1.16	0.98	-0.18	-1.45	0.11	1.3
Investment	0.88	0.62	-0.27	-2.38	1.15	0.97	-0.18	-1.64	0.09	1.67
Accruals	0.88	0.61	-0.27	-2.18	1.14	0.9	-0.24	-1.84	0.03	0.57
Risk	0.83	0.62	-0.22	-1.95	1.18	0.96	-0.22	-1.73	-0.01	-0.07

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Table C.8 – continued from previous page

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Value	0.85	0.68	-0.17	-1.65	1.27	0.98	-0.29	-2.37	-0.13	-1.16
Panel D: Total volume - ITM										
Aggregate	0.88	0.57	-0.31	-2.77	1.17	0.96	-0.21	-2.03	0.1	4.05
Momentum	0.85	0.43	-0.43	-3.54	1.19	1.05	-0.14	-1.18	0.28	3.71
Volatility	0.96	0.56	-0.39	-2.81	1.06	0.89	-0.17	-1.88	0.22	2.2
Profitability	0.79	0.42	-0.37	-2.66	1.19	1.01	-0.18	-1.69	0.19	1.85
Issuance	0.91	0.63	-0.28	-2.25	1.17	1.06	-0.11	-1.18	0.17	2.27
Accruals	0.88	0.55	-0.33	-2.75	1.14	0.89	-0.24	-2.07	0.08	1.59
Investment	0.88	0.58	-0.3	-2.58	1.15	0.93	-0.22	-2.08	0.08	1.44
Intangibles	1.01	0.73	-0.28	-2.43	1.16	0.95	-0.21	-1.84	0.07	0.82
Risk	0.83	0.57	-0.26	-2.26	1.18	0.97	-0.21	-1.78	0.05	0.59
Value	0.85	0.68	-0.18	-1.76	1.27	0.94	-0.34	-2.94	-0.16	-1.76
Panel E: Total volume - DITM										
Aggregate	0.88	0.66	-0.22	-2.07	1.17	1.03	-0.15	-1.52	0.08	3.03
Momentum	0.85	0.46	-0.39	-3.44	1.19	1.16	-0.04	-0.32	0.36	4.38
Profitability	0.79	0.4	-0.38	-2.72	1.19	1.12	-0.07	-0.76	0.31	2.88
Volatility	0.96	0.67	-0.29	-1.96	1.06	0.93	-0.13	-1.71	0.16	1.34
Issuance	0.91	0.76	-0.15	-1.32	1.17	1.07	-0.1	-1.26	0.05	0.71
Investment	0.88	0.71	-0.18	-1.59	1.15	1.01	-0.14	-1.39	0.03	0.74
Risk	0.83	0.66	-0.17	-1.71	1.18	1.04	-0.14	-1.22	0.03	0.4
Accruals	0.88	0.73	-0.15	-1.26	1.14	0.96	-0.18	-1.54	-0.03	-0.47
Intangibles	1.01	0.84	-0.18	-1.71	1.16	0.93	-0.23	-1.93	-0.05	-0.73
Value	0.85	0.74	-0.11	-1.23	1.27	1	-0.27	-2.3	-0.16	-1.5
Panel F: Call volume - DOTM										
Aggregate	0.88	0.53	-0.35	-3.91	1.17	0.92	-0.26	-3.39	0.09	2.91
Volatility	0.96	0.46	-0.49	-4.37	1.06	0.93	-0.13	-1.88	0.36	3.67
Issuance	0.91	0.55	-0.36	-3.37	1.17	1.01	-0.16	-2.37	0.2	2.52
Profitability	0.79	0.37	-0.42	-3.83	1.19	0.93	-0.26	-2.9	0.15	1.71
Investment	0.88	0.54	-0.34	-3.49	1.15	0.93	-0.22	-2.79	0.13	1.68
Momentum	0.85	0.46	-0.39	-4.01	1.19	0.93	-0.27	-2.95	0.12	1.62
Intangibles	1.01	0.67	-0.34	-3.37	1.16	0.91	-0.24	-2.46	0.09	0.83
Accruals	0.88	0.52	-0.36	-3.71	1.14	0.81	-0.33	-3.37	0.03	0.51
Risk	0.83	0.57	-0.26	-2.98	1.18	0.84	-0.34	-3.16	-0.08	-1.02
Value	0.85	0.63	-0.22	-2.36	1.27	0.96	-0.32	-3.33	-0.1	-0.88
Panel G: Call volume - OTM										
Aggregate	0.88	0.48	-0.4	-3.37	1.17	0.91	-0.27	-2.66	0.13	4.05
Volatility	0.96	0.42	-0.53	-3.66	1.06	0.9	-0.16	-1.86	0.37	3.65
Issuance	0.91	0.48	-0.43	-3.24	1.17	1.01	-0.16	-2.07	0.27	3.02
Profitability	0.79	0.28	-0.5	-3.31	1.19	0.95	-0.24	-2.25	0.27	2.64
Momentum	0.85	0.42	-0.43	-3.34	1.19	0.98	-0.21	-1.84	0.22	2.66
Investment	0.88	0.5	-0.38	-3.25	1.15	0.89	-0.26	-2.57	0.13	2.25

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Table C.8 – continued from previous page

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Accruals	0.88	0.5	-0.37	-2.98	1.14	0.82	-0.32	-2.57	0.06	0.94
Risk	0.83	0.5	-0.33	-3.02	1.18	0.87	-0.31	-2.43	0.02	0.27
Intangibles	1.01	0.66	-0.35	-3.24	1.16	0.78	-0.38	-2.99	-0.02	-0.29
Value	0.85	0.57	-0.28	-2.6	1.27	0.94	-0.33	-3.1	-0.05	-0.53
Panel H: Call volume - ATM										
Aggregate	0.88	0.62	-0.26	-2.03	1.17	1.03	-0.14	-1.22	0.12	3.44
Momentum	0.85	0.5	-0.35	-2.49	1.19	1.12	-0.08	-0.58	0.27	3.04
Issuance	0.91	0.62	-0.29	-2.07	1.17	1.12	-0.05	-0.48	0.24	2.7
Volatility	0.96	0.63	-0.32	-2.11	1.06	0.95	-0.11	-1.18	0.21	1.99
Profitability	0.79	0.46	-0.33	-1.98	1.19	1.05	-0.14	-1.16	0.19	1.53
Investment	0.88	0.61	-0.28	-2.17	1.15	1.02	-0.13	-1.06	0.14	2.73
Accruals	0.88	0.62	-0.25	-1.9	1.14	0.97	-0.16	-1.2	0.09	1.69
Value	0.85	0.66	-0.19	-1.65	1.27	1.09	-0.18	-1.37	0.01	0.08
Intangibles	1.01	0.84	-0.17	-1.34	1.16	0.95	-0.21	-1.58	-0.03	-0.35
Risk	0.83	0.66	-0.17	-1.36	1.18	0.98	-0.2	-1.46	-0.03	-0.36
Panel I: Call volume - ITM										
Aggregate	0.88	0.66	-0.22	-1.74	1.17	1.05	-0.12	-1.06	0.09	3.44
Momentum	0.85	0.5	-0.36	-2.62	1.19	1.13	-0.07	-0.49	0.29	3.82
Profitability	0.79	0.5	-0.28	-1.81	1.19	1.08	-0.11	-0.93	0.17	1.6
Volatility	0.96	0.68	-0.28	-1.91	1.06	0.94	-0.12	-1.14	0.16	1.58
Issuance	0.91	0.72	-0.19	-1.42	1.17	1.12	-0.05	-0.45	0.14	1.95
Investment	0.88	0.71	-0.18	-1.39	1.15	1.04	-0.11	-0.88	0.07	1.16
Accruals	0.88	0.67	-0.21	-1.63	1.14	0.99	-0.15	-1.14	0.06	1.16
Risk	0.83	0.66	-0.18	-1.41	1.18	1.06	-0.12	-0.88	0.06	0.76
Intangibles	1.01	0.86	-0.15	-1.2	1.16	0.97	-0.19	-1.43	-0.04	-0.38
Value	0.85	0.72	-0.14	-1.2	1.27	1.09	-0.18	-1.45	-0.05	-0.51
Panel J: Call volume - DITM										
Aggregate	0.88	0.71	-0.17	-1.35	1.17	1.07	-0.11	-0.87	0.07	2.65
Momentum	0.85	0.49	-0.37	-2.66	1.19	1.21	0.01	0.11	0.38	4.53
Profitability	0.79	0.52	-0.26	-1.65	1.19	1.11	-0.09	-0.73	0.18	1.75
Volatility	0.96	0.68	-0.28	-1.71	1.06	0.94	-0.12	-1.35	0.15	1.31
Issuance	0.91	0.79	-0.12	-0.87	1.17	1.14	-0.03	-0.28	0.09	1.31
Investment	0.88	0.74	-0.14	-1.08	1.15	1.06	-0.09	-0.66	0.05	0.97
Accruals	0.88	0.75	-0.12	-0.87	1.14	1.02	-0.12	-0.81	0.01	0.16
Risk	0.83	0.73	-0.11	-0.94	1.18	1.05	-0.13	-0.94	-0.02	-0.3
Value	0.85	0.73	-0.12	-1.16	1.27	1.14	-0.14	-0.94	-0.02	-0.17
Intangibles	1.01	0.98	-0.04	-0.28	1.16	0.89	-0.27	-1.91	-0.23	-2.72
Panel K: Put volume - DOTM										
Aggregate	0.88	0.6	-0.28	-2.15	1.17	0.93	-0.25	-2.03	0.03	1.29
Momentum	0.85	0.45	-0.4	-2.8	1.19	1.03	-0.16	-1.2	0.24	2.52
Profitability	0.79	0.42	-0.36	-2.24	1.19	0.98	-0.21	-1.75	0.15	1.31

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Table C.8 – continued from previous page

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Volatility	0.96	0.61	-0.35	-2.12	1.06	0.86	-0.2	-2.15	0.15	1.2
Issuance	0.91	0.62	-0.3	-1.97	1.17	1	-0.17	-1.83	0.12	1.6
Investment	0.88	0.61	-0.28	-2.03	1.15	0.93	-0.22	-1.76	0.06	1.11
Risk	0.83	0.57	-0.26	-2.37	1.18	0.95	-0.23	-1.62	0.03	0.45
Intangibles	1.01	0.76	-0.25	-2	1.16	0.87	-0.29	-1.87	-0.04	-0.45
Accruals	0.88	0.64	-0.24	-1.69	1.14	0.82	-0.32	-2.23	-0.08	-1.55
Value	0.85	0.73	-0.12	-1.05	1.27	0.91	-0.37	-2.59	-0.24	-2.22
Panel L: Put volume - OTM										
Aggregate	0.88	0.57	-0.31	-2.77	1.17	0.91	-0.26	-2.53	0.05	1.87
Profitability	0.79	0.36	-0.42	-2.9	1.19	1	-0.19	-1.79	0.24	2.22
Momentum	0.85	0.44	-0.41	-3.35	1.19	1.01	-0.18	-1.53	0.23	2.53
Volatility	0.96	0.58	-0.38	-2.6	1.06	0.88	-0.18	-2.08	0.19	1.74
Issuance	0.91	0.62	-0.29	-2.31	1.17	0.99	-0.19	-2.13	0.11	1.34
Intangibles	1.01	0.68	-0.33	-3.08	1.16	0.89	-0.27	-2.14	0.06	0.65
Risk	0.83	0.55	-0.29	-2.73	1.18	0.92	-0.26	-2.04	0.03	0.38
Investment	0.88	0.59	-0.3	-2.51	1.15	0.87	-0.28	-2.59	0.02	0.44
Accruals	0.88	0.61	-0.27	-2.34	1.14	0.85	-0.29	-2.42	-0.03	-0.56
Value	0.85	0.73	-0.12	-1.2	1.27	0.8	-0.47	-3.64	-0.35	-2.94
Panel M: Put volume - ATM										
Aggregate	0.88	0.53	-0.35	-3.49	1.17	0.88	-0.29	-3.2	0.06	2.38
Volatility	0.96	0.49	-0.47	-3.19	1.06	0.89	-0.17	-2.31	0.3	2.41
Profitability	0.79	0.36	-0.43	-3.04	1.19	0.94	-0.25	-3.03	0.18	1.6
Issuance	0.91	0.52	-0.39	-3.53	1.17	0.95	-0.22	-2.93	0.17	2.48
Intangibles	1.01	0.62	-0.39	-3.69	1.16	0.92	-0.23	-2.02	0.15	2.12
Momentum	0.85	0.44	-0.42	-3.48	1.19	0.93	-0.27	-2.76	0.15	1.8
Investment	0.88	0.55	-0.33	-3.31	1.15	0.83	-0.32	-3.46	0.01	0.17
Risk	0.83	0.54	-0.29	-3.28	1.18	0.88	-0.3	-2.61	-0.01	-0.1
Accruals	0.88	0.57	-0.31	-3.22	1.14	0.79	-0.35	-3.07	-0.04	-0.73
Value	0.85	0.67	-0.18	-2.05	1.27	0.81	-0.47	-3.67	-0.29	-2.57
Panel N: Put volume - ITM										
Aggregate	0.88	0.45	-0.43	-5.74	1.17	0.83	-0.34	-5.15	0.1	4.01
Volatility	0.96	0.43	-0.53	-5.33	1.06	0.86	-0.21	-3.01	0.33	3.52
Profitability	0.79	0.21	-0.58	-6.11	1.19	0.89	-0.3	-4.16	0.28	3.52
Momentum	0.85	0.34	-0.51	-5.27	1.19	0.91	-0.29	-3.99	0.22	2.56
Intangibles	1.01	0.57	-0.44	-5.1	1.16	0.9	-0.26	-2.89	0.18	1.75
Issuance	0.91	0.47	-0.45	-5.55	1.17	0.89	-0.28	-4.25	0.17	2.62
Investment	0.88	0.48	-0.41	-5.05	1.15	0.8	-0.35	-5.24	0.05	0.85
Accruals	0.88	0.47	-0.41	-4.92	1.14	0.74	-0.4	-5.03	0.01	0.29
Risk	0.83	0.47	-0.36	-4.48	1.18	0.81	-0.37	-4.13	-0	-0.05
Value	0.85	0.61	-0.24	-3.4	1.27	0.74	-0.53	-5.38	-0.29	-3.11
Panel O: Put volume - DITM										

Continued on next page

Table C.8 – continued from previous page

Cluster	R^S	$R^S_{Q5(O/S)}$	OTP_S	t	R^L	$R^L_{Q5(O/S)}$	OTP_L	t	OTP	t
Aggregate	0.88	0.57	-0.31	-3.57	1.17	0.91	-0.26	-3.77	0.05	1.78
Volatility	0.96	0.61	-0.35	-2.98	1.06	0.91	-0.15	-2.33	0.2	1.93
Momentum	0.85	0.46	-0.39	-3.72	1.19	0.96	-0.23	-2.9	0.16	2.01
Profitability	0.79	0.39	-0.4	-3.49	1.19	0.95	-0.25	-3.18	0.15	1.66
Intangibles	1.01	0.68	-0.33	-3.86	1.16	0.97	-0.19	-2.04	0.14	1.6
Issuance	0.91	0.6	-0.31	-3.24	1.17	0.96	-0.21	-3.14	0.1	1.3
Investment	0.88	0.58	-0.31	-3.23	1.15	0.88	-0.27	-3.65	0.03	0.57
Accruals	0.88	0.57	-0.31	-3.26	1.14	0.84	-0.3	-3.72	0.01	0.22
Risk	0.83	0.55	-0.28	-3.25	1.18	0.91	-0.27	-3.13	0.01	0.16
Value	0.85	0.69	-0.16	-1.84	1.27	0.83	-0.44	-4.5	-0.29	-2.95

C.3.2 Sign-Restricted SVAR Framework

This subsection describes the sign-restricted structural vector autoregression (SVAR) used to identify option demand shocks for end users and market makers. The framework exploits joint information from option prices and quantities and the zero–net-supply nature of option markets.

C.3.2.1 Option Price Proxy: Semivariance Premia

Construction and interpretation. We use semivariance premia, as in Kilic and Shaliastovich (2019) and Held et al. (2020), as measures for the expensiveness of call and put options, to allow a distinction between the two channels. Intuitively, an upper (lower) semivariance premium is given by the difference between the option-implied variances from at-the-money and out-of-the-money call (put) options and the variance in the positive (negative) return domain under the physical measure. High semivariance premia indicate that calls/puts are expensive vis-a-vis the characteristics of the underlying (especially its variance), hinting at a heightened demand for the option.

The upper (lower) semivariance of a random variable Z is defined as the expected squared difference between Z and its mean, conditional on that difference being positive (negative). For logarithmic stock returns, Kilic and Shaliastovich (2019) and Held et al. (2020) show how to decompose the expression for the model-free option-implied variance (see Bakshi et al., 2003; Carr and Madan, 2001) into the lower semivariance $SV_t^{\mathbb{Q}-}$ and the upper semivariance $SV_t^{\mathbb{Q}+}$ under the risk-neutral measure $\mathbb{Q}$:

$$SV_t^{\mathbb{Q}-} = \int_0^{S_t(1+r_{t,T})} \frac{2(1+\log(S_t(1+r_{t,T})/X))}{X^2} P_t(T-t,X)dX \tag{C.1}$$

$$SV_t^{\mathbb{Q}+} = \int_{S_t(1+r_{t,T})}^{\infty} \frac{2(1-\log(X/S_t(1+r_{t,T})))}{X^2} C_t(T-t,X)dX. \tag{C.2}$$

In these expressions, $C_t(T-t, X)$ and $P_t(T-t, X)$ denote the prices of European call and put options, respectively, with strike price X and time-to-maturity $T-t$.

Empirical measurement. To empirically estimate the option-implied semivariances, we follow the methodologies outlined in Carr and Wu (2009) and Chang et al. (2012). Specifically, we use the volatility surface file provided by OptionMetrics. It provides implied volatilities for standardized ranges of maturities and option deltas, calculated by interpolating the implied volatilities of available options, calculated from binomial trees.

We compute ex-dividend stock prices and derive implied volatilities with a fixed maturity of 30 days. We only consider out-of-the-money (OTM) options. To include a stock-day in our sample, we require a minimum of four distinct call or put implied volatilities, each exceeding zero.

Moneyness is defined as the ratio of the strike price to the ex-dividend stock price. To obtain a continuum of 1000 implied volatilities, we apply a cubic smoothing spline across moneyness values ranging from 0.3% to 300%. Following Jiang and Tian (2005), to address potential interpolation and extrapolation issues, we set the implied volatilities for moneyness levels beyond the observed range in the OptionMetrics data to the corresponding implied volatilities at the boundary moneyness values. Equipped with a continuum of implied volatilities, we then calculate Black and Scholes (1973) option prices. Finally, we implement the trapezoidal rule to numerically compute the risk-neutral semivariances in equation C.1 and equation C.2.

To estimate semivariances under the physical measure $\mathbb{P}$, we again follow Kilic and Shaliastovich (2019) and use the fitted value from a time series model. In particular, we generalize the approach of Bekaert and Hoerova (2014) to semivariances by running the following predictive time series regressions on daily stock return data from the OptionMetrics daily price file:

$$\begin{aligned} RV^-_{t+1,t+22} = a^- &+ b^-_1 SV^{\mathbb{Q}-}_t + b^-_2 SV^{\mathbb{Q}+}_t + b^-_3 RV^-_{t-21,t} + b^-_4 RV^+_{t-21,t} \\ &+ b^-_5 RV^-_{t-4,t} + b^-_6 RV^+_{t-4,t} + b^-_7 RV^-_{t,t} + b^-_8 RV^+_{t,t} + \varepsilon^-_{t+1,t+22} \end{aligned} \tag{C.3}$$

$$\begin{aligned} RV^+_{t+1,t+22} = a^+ &+ b^+_1 SV^{\mathbb{Q}-}_t + b^+_2 SV^{\mathbb{Q}+}_t + b^+_3 RV^-_{t-21,t} + b^+_4 RV^+_{t-21,t} \\ &+ b^+_5 RV^-_{t-4,t} + b^+_6 RV^+_{t-4,t} + b^+_7 RV^-_{t,t} + b^+_8 RV^+_{t,t} + \varepsilon^+_{t+1,t+22} \end{aligned} \tag{C.4}$$

where $RV^*_{t_1,t_2}$ with $t_1 < t_2$ and $* \in \{-,+\}$ is defined by

$$RV^+_{t_1,t_2} = \sum_{t=t_1}^{t_2} r_t^2 1_{r_t>0} \quad \text{and} \quad RV^-_{t_1,t_2} = \sum_{t=t_1}^{t_2} r_t^2 1_{r_t<0} \tag{C.5}$$

We calculate expectations for the next 22 trading days, which is equivalent to the 30 days-to-maturity convention of OptionMetrics. We run regressions C.3 and C.4 separately for each stock using the full sample period. We use the estimated coefficients to estimate the semivariances for each stock on each day t and $* \in \{-,+\}$ as

$$\begin{aligned} SV^{\mathbb{P}*}_{t:T} = \alpha^* &+ \beta^*_1 SV^{\mathbb{Q}-}_{t:T} + \beta^*_2 SV^{\mathbb{Q}+}_{t:T} + \beta^*_3 RV^-_{i,t-21:t} + \beta^*_4 RV^+_{i,t-21:t} \\ &+ \beta^*_5 RV^-_{i,t-4:t} + \beta^*_6 RV^+_{i,t-4:t} + \beta^*_7 RV^-_{i,t} + \beta^*_8 RV^+_{i,t} \end{aligned} \tag{C.6}$$

we compute daily stock-specific semivariance risk premia as

$$SVP^P_{t:T} = SV^{\mathbb{Q}-}_{t:T} - SV^{\mathbb{P}-}_{t:T} \quad \text{and} \quad SVP^C_{t:T} = SV^{\mathbb{Q}+}_{t:T} - SV^{\mathbb{P}+}_{t:T}. \tag{C.7}$$

In our later analysis, $SVP^P_{i,t:T}$ is interpreted as a measure for the expensiveness of put options and $SVP^C_{i,t:T}$ is our measure for the expensiveness of call options for stock i on day t.

C.3.2.2 Option Quantity Proxy: Delta-Weighted Inventory

We use open-close transaction data from multiple U.S. option exchanges: the International Securities Exchange (ISE), Chicago Board Options Exchange (CBOE), Nasdaq Options Trade Outline (NOTO), PHLX Options Trade Outline (PHOTO), and ISE Gemini. These data sets provide daily volumes of opening and closing trades, disaggregated into buys and sells, and categorized by five trader types: *Customer*, *Professional Customer*, *Broker-Dealer*, *Firm*, and *Market Maker*.[13]

Similar to Almeida and Freire (2023), we define the *Option End-Users* as the combined group of *Customers*, *Professional Customers*, and *Firms*, who are typically viewed as informed or speculative participants. We focus on these traders' call and put option holdings. To characterize both the direction and magnitude of option holdings by end users, we construct a measure of *delta-weighted option inventory*.

For each option series j written on underlying stock s, and for each trader category i, we construct a daily *delta-weighted order imbalance*. Let $Buy_{i,j,t}$ and $Sell_{i,j,t}$ denote the buy and sell volumes of trader type i in option series j on day t. The order imbalance is defined as

$$OI_{i,j,t} = \left(Buy_{i,j,t} - Sell_{i,j,t}\right) \cdot S_{s,t} \cdot |\Delta_{j,t}|, \tag{C.8}$$

where $S_{s,t}$ is the contemporaneous price of the underlying stock and $|\Delta_{j,t}|$ is the absolute delta of option series j taken from OptionMetrics. We interpret $OI_{i,j,t}$ as the daily change in delta-adjusted option inventory, expressed in underlying-equivalent units, for trader type i in option series j. Scaling by the underlying stock price expresses these exposures in dollar terms, which facilitates comparability across stocks.

The cumulative inventory associated with this series is obtained by aggregating order imbalances over time:

$$INV_{i,j,t} = \sum_{\tau \le t} OI_{i,j,\tau}. \tag{C.9}$$

Finally, we aggregate inventories across end-user trader types and option series to the stock-day level. For each stock s and day t, we sum $INV_{i,j,t}$ across all option series of a given type $k \in \{\text{Call}, \text{Put}\}$:

$$INV^k_{s,t} = \sum_{j \in \mathcal{J}^k_{s,t}} \sum_{i \in \mathcal{I}} Inv_{i,j,t}, \tag{C.10}$$

where $\mathcal{J}^k_{s,t}$ denotes the set of active option series of type k written on stock s at time t, and $\mathcal{I}$ is the set of option end-user trader categories. The resulting measures, $INV^C_{s,t}$ and

[13] For detailed definitions of trader categories, see e.g., `https://datashop.cboe.com/Themes/Livevol_v2/Content/static/C1OpenCloseSpecification.pdf`

$INV^P_{s,t}$, summarize the aggregate delta-adjusted option inventories of end users at the stock-day frequency.

C.3.2.3 Structural and Reduced-Form Representation

We model the contemporaneous interaction between prices and quantities through a structural system of demand equations. Let

$$\mathbf{P}_t = \boldsymbol{B}\mathbf{Q}_t + \boldsymbol{\varepsilon}_t, \tag{C.11}$$

where $\mathbf{P}_t = [P_{MM,t},\, P_{EU,t}]'$ denotes prices charged by market makers (MM) and paid by end users (EU), $\mathbf{Q}_t = [Q_{MM,t},\, Q_{EU,t}]'$ denotes the corresponding quantities, and $\boldsymbol{\varepsilon}_t = [\varepsilon^D_{MM,t},\, \varepsilon^D_{EU,t}]' \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ represents mutually orthogonal structural demand shocks originating from market makers and end users.

Because the structural system in equation (C.11) is not directly observable, we begin by estimating a reduced-form VAR for equilibrium prices and quantities:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\Phi}\mathbf{Y}_{t-1} + \mathbf{u}_t, \tag{C.12}$$

where $\mathbf{Y}_t = [P_t,\, Q_t]'$ collects the observable equilibrium price and quantity, and $\mathbf{u}_t$ denotes reduced-form innovations.[14]

The reduced-form residuals $\mathbf{u}_t$ are linear combinations of the underlying structural shocks and therefore do not admit a direct economic interpretation.

C.3.2.4 Identification via Sign Restrictions

Structural identification requires recovering an impact matrix $\mathbf{A}$ such that

$$\mathbf{u}_t = \mathbf{A}\boldsymbol{\varepsilon}_t, \tag{C.13}$$

or equivalently $\boldsymbol{\varepsilon}_t = \mathbf{A}^{-1}\mathbf{u}_t$. The key identification challenge is to disentangle market-maker and end-user demand shocks from the reduced-form innovations.

We impose sign restrictions on the contemporaneous price and quantity responses implied by $\mathbf{A}$, motivated by standard supply-and-demand considerations in markets with zero net supply. Specifically, we require

$$\text{sign}(\mathbf{A}) = \begin{bmatrix} + & + \\ - & + \end{bmatrix}, \tag{C.14}$$

[14] Following Jacobs et al. (2026), we treat end-user quantity as the equilibrium quantity.

where rows correspond to price and quantity responses, and columns correspond to market-maker and end-user demand shocks, respectively.

These restrictions imply that a positive end-user demand shock raises both option prices and quantities, whereas a positive market-maker demand shock raises prices but reduces equilibrium quantities. This pattern is consistent with downward-sloping demand and upward-sloping supply curves.[15]

C.3.2.5 Covariance Restrictions and Model Space

Let $\Sigma(\mathbf{u}_t)$ denote the covariance matrix of the reduced-form innovations. Equation (C.13) implies the covariance restriction

$$\Sigma(\mathbf{u}_t) = \mathbf{A}\mathbf{A}'. \tag{C.15}$$

Let $\mathbf{L}$ denote the lower-triangular Cholesky factor of $\Sigma(\mathbf{u}_t)$, such that $\Sigma(\mathbf{u}_t) = \mathbf{L}\mathbf{L}'$. Then any admissible impact matrix $\mathbf{A}$ satisfying the covariance restriction can be written as

$$\mathbf{A} = \mathbf{L}\mathbf{Q}, \tag{C.16}$$

where $\mathbf{Q}$ is an orthonormal matrix satisfying $\mathbf{Q}\mathbf{Q}' = \mathbf{I}$.

This decomposition provides a convenient parametrization of the set of observationally equivalent structural models. The orthonormal matrix $\mathbf{Q}$ rotates the baseline Cholesky identification to generate alternative impact matrices that preserve the reduced-form covariance structure.

C.3.2.6 Bayesian Estimation and Model Selection

To account for parameter uncertainty in the reduced-form VAR, we adopt a Bayesian estimation approach. We assume a Normal–Inverse–Wishart prior for $(\mathbf{\Phi}, \Sigma)$ in equation (C.12) and draw 100 realizations $\{(\mathbf{\Phi}^{(l)}, \Sigma^{(l)})\}_{l=1}^{100}$ from the posterior distribution.

For each posterior draw, we generate 100 candidate impact matrices $\mathbf{A} = \mathbf{L}\mathbf{Q}$ by drawing random orthonormal matrices $\mathbf{Q}$ and retain only those that satisfy the sign restrictions in equation (C.14).

Following Fry and Pagan (2011), we summarize the identified set by computing the element-wise median impact matrix $\mathbf{A}_{\text{med}}$ across all models in $\mathcal{G}$. We then select the single model $\hat{g} \in \mathcal{G}$

[15] By market clearing, a market-maker demand shock corresponds to an offsetting supply shock from end users, i.e., $\varepsilon^D_{MM} = -\varepsilon^S_{EU}$. A positive supply shock from end users increases quantities and lowers prices, implying that a positive market-maker demand shock must decrease quantities and increase prices.

that minimizes the squared distance to this median target:

$$\hat{g} = \arg\min_{g \in \mathcal{G}} \left\| \mathbf{A}_g - \mathbf{A}_{\text{med}} \right\|^2 . \tag{C.17}$$

Structural demand shocks are recovered using the impact matrix $\mathbf{A}_{\hat{g}}$ associated with the selected model.

Bibliography

Abhyankar, Abhay, Ilias Filippou, and Pedro A Garcia-Ares (2024). Overcoming Arbitrage Limits: Option Trading and Momentum Returns. *Journal of Financial and Quantitative Analysis* 59 (1), 97–120.

Adrian, Tobias, Erkko Etula, and Tyler Muir (2014). Financial Intermediaries and the Cross-Section of Asset Returns. *The Journal of Finance* 69 (6), 2557–2596.

Almeida, Caio and Gustavo Freire (2023). Demand in the Option Market and the Pricing Kernel. Working Paper.

Amihud, Yakov (2002). Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5 (1), 31–56.

Arnott, Robert D, Campbell R Harvey, Vitali Kalesnik, and Juhani T Linnainmaa (2021). Reports of Value's Death May Be Greatly Exaggerated. *Financial Analysts Journal* 77 (1), 44–67.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan (2003). Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options. *The Review of Financial Studies* 16 (1), 101–143.

Bali, Turan G., Heiner Beckmeyer, and Timo Wiedemann (2023). Expected Mispricing. Working Paper.

Bali, Turan G. and Armen Hovakimian (2009). Volatility Spreads and Expected Stock Returns. *Management Science* 55, 1797–1812.

Ball, Ray, Joseph Gerakos, Juhani T Linnainmaa, and Valeri Nikolaev (2016). Accruals, Cash Flows, and Operating Profitability in the Cross Section of Stock Returns. *Journal of Financial Economics* 121 (1), 28–45.

Bekaert, Geert and Marie Hoerova (2014). The VIX, the Variance Premium and Stock Market Volatility. *Journal of Econometrics* 183 (2), 181–192.

Bernile, Gennaro, Jianfeng Hu, Guangzhong Li, and Roni Michaely (2025). Information Spillover and Corporate Policies: The Case of Listed Options. *Journal of Financial and Quantitative Analysis* 60 (1), 447–481.

Biais, B. and P. Hillion (1994). Insider and Liquidity Trading in Stock and Options Markets. *The Review of Financial Studies* 7, 743–780.

Binsbergen, Jules H. Van, Martijn Boons, Christian C. Opp, and Andrea Tamoni (2023). Dynamic Asset (Mis) Pricing: Build-Up Versus Resolution Anomalies. *Journal of Financial Economics* 147 (2), 406–431.

Black, Fischer (1975). Fact and Fantasy in the Use of Options. *Financial Analysts Journal* 31 (4), 36–41.

Black, Fischer and Myron Scholes (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81 (3), 637–654.

Blanco, Iván and David Wehrheim (2017). The Bright Side of Financial Derivatives: Options Trading and Firm Innovation. *Journal of Financial Economics* 125 (1), 99–119.

Böll, Julian, Fanchen Meng, Julian Thimme, and Marliese Uhrig-Homburg (2024). Option Trading-Implied Prevalence of Asset Pricing Anomalies.

— (2025). How Option Traders Take Sides on Return Predictability. Working Paper.

Böll, Julian, Julian Thimme, and Marliese Uhrig-Homburg (2022). Anomalies and Optionability. Working Paper.

Bollen, Nicolas PB and Robert E Whaley (2004). Does Net Buying Pressure Affect the Shape of Implied Volatility Functions? *The Journal of Finance* 59 (2), 711–753.

Brunnermeier, Markus K and Lasse Heje Pedersen (2009). Market Liquidity and Funding Liquidity. *The Review of Financial Studies* 22 (6), 2201–2238.

Cao, H. Henry (1999). The Effect of Derivative Assets on Information Acquisition and Price Behavior in a Rational Expectations Equilibrium. *The Review of Financial Studies* 12, 131–163.

Cao, Jie, Amit Goyal, Sai Ke, and Xintong Zhan (2024). Options Trading and Stock Price Informativeness. *Journal of Financial and Quantitative Analysis* 59 (4), 1516–1540.

Cao, Zhen, Surya Chelikani, Osman Kilic, and Xuewu Wang (2022). Implied Volatility Spread and Stock Mispricing. *Journal of Behavioral Finance*, 1–13.

Carr, Peter and Dilip Madan (2001). Optimal Positioning in Derivative Securities. *Quantitative Finance* 1 (1), 19–37.

Carr, Peter and Liuren Wu (2009). Variance Risk Premiums. *The Review of Financial Studies* 22 (3), 1311–1341.

Chakravarty, Sugato, Huseyin Gulen, and Stewart Mayhew (2004). Informed Trading in Stock and Option Markets. *The Journal of Finance* 59, 1235–1257.

Chang, Bo-Young, Peter Christoffersen, Kris Jacobs, and Gregory Vainberg (2012). Option-Implied Measures of Equity Risk. *Review of Finance* 16 (2), 385–428.

Chen, Andrew Y, Alejandro Lopez-Lira, and Tom Zimmermann (2023). Peer-Reviewed Theory Does Not Help Predict The Cross-Section of Stock Returns. Working Paper.

Chen, Andrew Y. and Tom Zimmermann (2022). Open Source Cross-Sectional Asset Pricing. *Critical Finance Review* 27 (2), 207–264.

Cochrane, John H (1991). Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations. *The Journal of Finance* 46 (1), 209–237.

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels (2013). Ex Ante Skewness and Expected Stock Returns. *The Journal of Finance* 68, 85–124.

Corwin, Shane A and Paul Schultz (2012). A Simple Way to Estimate Bid-Ask Spreads From Daily High and Low Prices. *The Journal of Finance* 67, 719–760.

Cremers, Martijn and David Weinbaum (2010). Deviations from Put-Call Parity and Stock Return Predictability. *Journal of Financial and Quantitative Analysis* 45, 335–367.

Da, Zhi, Xi Dong, Ke Wu, and Dexin Zhou (2024). Inside and Outside Informed Trading.

Danielsen, Bartley R. and Sorin M. Sorescu (2001). Why Do Option Introductions Depress Stock Prices? A Study of Diminishing Short Sale Constraints. *Journal of Financial and Quantitative Analysis* 36, 451–484.

Davis, James L, Eugene F Fama, and Kenneth R French (2000). Characteristics, Covariances, and Average Returns: 1929 to 1997. *The Journal of Finance* 55 (1), 389–406.

Diamond, Douglas W. (1985). Optimal Release of Information By Firms. *The Journal of Finance* 40, 1071–1094.

Diamond, Douglas W and Robert E Verrecchia (1987). Constraints on Short-Selling and Asset Price Adjustment to Private Information. *Journal of Financial Economics* 18 (2), 277–311.

Drechsler, Itamar and Qingyi Freda Drechsler (2021). The Shorting Premium and Asset Pricing Anomalies. Working Paper.

Easley, David, Maureen O'hara, and Pulle Subrahmanya Srinivas (1998). Option Volume and Stock Prices: Evidence on Where Informed Traders Trade. *The Journal of Finance* 53 (2), 431–465.

Eisfeldt, Andrea L, Edward Kim, and Dimitris Papanikolaou (2020). Intangible Value. Working Paper.

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff (2018). Anomalies and News. *The Journal of Finance* 73 (5), 1971–2001.

Fama, Eugene F and Kenneth R French (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance* 47 (2), 427–465.

— (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33, 3–53.

Figlewski, Stephen and Gwendolyn P Webb (1993). Options, Short Sales, and Market Completeness. *The Journal of Finance* 48, 761–777.

Frazzini, Andrea and Lasse Heje Pedersen (2022). Embedded Leverage. *The Review of Asset Pricing Studies* 12 (1), 1–52.

Frey, Jonas (2023). Which Stock Return Predictors Reflect Mispricing? Working Paper.

Fry, Renee and Adrian Pagan (2011). Sign Restrictions in Structural Vector Autoregressions: A Critical Review. *Journal of Economic Literature* 49 (4), 938–960.

Garleanu, Nicolae, Lasse Heje Pedersen, and Allen M Poteshman (2009). Demand-Based Option Pricing. *The Review of Financial Studies* 22 (10), 4259–4299.

Ge, Li, Tse-Chun Lin, and Neil D. Pearson (2016). Why Does the Option to Stock Volume Ratio Predict Stock Returns? *Journal of Financial Economics* 120 (3), 601–622.

Goldberg, Jonathan and Yoshio Nozawa (2021). Liquidity Supply in the Corporate Bond Market. *The Journal of Finance* 76 (2), 755–796.

Gonçalves, Andrei S and Gregory Leonard (2023). The Fundamental-to-Market Ratio and the Value Premium Decline. *Journal of Financial Economics* 147 (2), 382–405.

Götz, Alexander, Ryan Riordan, Philipp Schuster, and Marliese Uhrig-Homburg (2025). Measuring Option Liquidity. Working Paper.

Goyal, Amit and Alessio Saretto (2009). Cross-Section of Option Returns and Volatility. *Journal of Financial Economics* 94 (2), 310–326.

Haddad, Valentin and Tyler Muir (2021). Do Intermediaries Matter for Aggregate Asset Prices? *The Journal of Finance* 76 (6), 2719–2761.

Han, Yufeng, Dashan Huang, Dayong Huang, and Guofu Zhou (2022). Expected Return, Volume, and Mispricing. *Journal of Financial Economics* 143 (3), 1295–1315.

Han, Yufeng, Dayong Huang, and Xiao Xiao (2024). Options Traders, Reversals, and Stock Returns.

He, Zhiguo, Bryan Kelly, and Asaf Manela (2017). Intermediary Asset Pricing: New Evidence From Many Asset Classes. *Journal of Financial Economics* 126 (1), 1–35.

He, Zhiguo and Arvind Krishnamurthy (2013). Intermediary Asset Pricing. *American Economic Review* 103, 732–770.

Held, Matthias, Julia Kapraun, Marcel Omachel, and Julian Thimme (2020). Up-and Downside Variance Risk Premia in Global Equity Markets. *Journal of Banking & Finance* 118, 105875.

Hiraki, Kazuhiro and George S Skiadopoulos (2021). The Contribution of Frictions to Expected Returns: An Options-Based Estimation Approach. Working Paper.

Hollstein, Fabian and Chardin Wese Simen (2020). Variance Risk: A Bird's Eye View. *Journal of Econometrics* 215 (2), 517–535.

Hollstein, Fabian and Chardin Wese Simen (2024). How Do Investors Trade Option Anomalies?

Hou, Kewei, Chen Xue, and Lu Zhang (2015). Digesting Anomalies: An Investment Approach. *The Review of Financial Studies* 28 (3), 650–705.

— (2020). Replicating Anomalies. *The Review of Financial Studies* 33, 2019–2133.

Hu, Jianfeng (2014). Does Option Trading Convey Stock Price Information? *Journal of Financial Economics* 111, 625–645.

— (2018). Option Listing and Information Asymmetry. *Review of Finance* 22, 1153–1194.

Jacobs, Heiko and Sebastian Müller (2020). Anomalies Across the Globe: Once Public, No Longer Existent? *Journal of Financial Economics* 135 (1), 213–230.

Jacobs, Kris, Anh Thu Mai, and Paola Pederzoli (2026). Identifying Demand Curves in Index Option Markets. *Management Science*.

Jennings, Robert and Laura Starks (1986). Earnings Announcements, Stock Price Adjustment, and the Existence of Option Markets. *The Journal of Finance* 41 (1), 107–125.

Jensen, Theis Ingerslev, Bryan Kelly, and Lasse Heje Pedersen (2023). Is There a Replication Crisis in Finance? *The Journal of Finance* 78 (5), 2465–2518.

Jiang, George J and Yisong S Tian (2005). The Model-Free Implied Volatility and its Information Content. *The Review of Financial Studies* 18 (4), 1305–1342.

Johnson, Travis L. and Eric C. So (2012). The Option to Stock Volume Ratio and Future Returns. *Journal of Financial Economics* 106, 262–286.

Kilic, Mete and Ivan Shaliastovich (2019). Good and Bad Variance Premia and Expected Returns. *Management Science* 65 (6), 2522–2544.

Mayhew, Stewart and Vassil Mihov (2004). How Do Exchanges Select Stocks for Option Listing? *The Journal of Finance* 59, 447–471.

McLean, R David and Jeffrey Pontiff (2016). Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance* 71 (1), 5–32.

McLean, R David, Jeffrey Pontiff, and Christopher Reilly (2020). Taking Sides on Return Predictability. Working Paper.

Muravyev, Dmitriy and Neil D Pearson (2020). Options Trading Costs are Lower Than You Think. *The Review of Financial Studies* 33 (11), 4973–5014.

Muravyev, Dmitriy, Neil D Pearson, and Joshua M Pollet (2025a). Anomalies and Their Short-Sale Costs. *The Journal of Finance* 80 (6), 3639–3694.

— (2025b). Why Does Options Market Information Predict Stock Returns? *Journal of Financial Economics* 172, 104153.

Newey, Whitney K. and Kenneth D. West (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55, 703–708.

Ofek, Eli, Matthew Richardson, and Robert F. Whitelaw (2004). Limited Arbitrage and Short Sales Restrictions: Evidence From the Options Markets. *Journal of Financial Economics* 74 (2), 305–342.

Pan, Jun and Allen M. Poteshman (2006). The Information in Option Volume for Future Stock Prices. *The Review of Financial Studies* 19, 871–908.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam (2009). Options Trading Activity and Firm Valuation. *Journal of Financial Economics* 94, 345–360.

— (2010). O/S: The Relative Trading Activity in Options and Stock. *Journal of Financial Economics* 96, 1–17.

Schwert, G William (2003). Anomalies and Market Efficiency. *Handbook of the Economics of Finance* 1, 939–974.

Skinner, Douglas J (1989). Options Markets and Stock Return Volatility. *Journal of Financial Economics* 23 (1), 61–78.

— (1990). Options Markets and the Information Content of Accounting Earnings Releases. *Journal of Accounting and Economics* 13 (3), 191–211.

Stiglitz, Joseph E. and Andrew Weiss (1981). Credit Rationing in Markets with Imperfect Information. *American Economic Review* 71, 393–410.

Xing, Yuhang, Xiaoyan Zhang, and Rui Zhao (2010). What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns? *Journal of Financial and Quantitative Analysis* 45, 641–662.