Following the Footprints: Towards a Taxonomy of the Factor Zoo*

Julian Böll‡ Fanchen Meng§ Julian Thimme¶ Marliese Uhrig-Homburg‖

This version: April 23, 2024

Abstract

Options on individual stocks can be used to trade against mispricings associated with various cross-sectional asset pricing anomalies. Based on this insight, we propose an option volume implied mispricing score ($OVIMS$) that is supposed to gauge the degree to which an anomaly is linked to stock mispricing. Anomalies in the categories of "momentum" and "profitability" are consistently found among those with high mispricing scores. We replicate stock positions with options and find large price wedges between option-implied synthetic and physical stock positions for anomalies characterized by high $OVIMS$. These disparities suggest that sophisticated traders strategically employ options to trade against prevailing stock mispricings. For certain high $OVIMS$ anomalies, we find empirical evidence that the demand for options is driven by proprietary traders of financial institutions. Furthermore, our findings indicate that traders build option positions particularly during periods of heightened market frictions, where mispricing is particularly pronounced.

Keywords: Asset pricing · Anomalies · Mispricing · Options

JEL: G11 · G12 · G14

*We are grateful for comments from Heiner Beckmeyer, Martijn F. Boons, Nicole Branger, Andrew Y. Chen, Jan Harren, Dmitriy Muravyev, Tobias Sichert (discussant), Rüdiger Weber, Timo Wiedemann and seminar participants at the Theory-based Empirical Asset Pricing Research (TBEAR) Network Workshop 2024 as well as KIT. The authors gratefully acknowledge financial support from the German Research Foundation as part of the research group FOR5230 *Financial markets and frictions - An intermediary asset pricing approach*.

‡Karlsruhe Institute of Technology, Germany, Email: julian.boell@kit.edu.

§Karlsruhe Institute of Technology, Germany, Email: fanchen.meng@kit.edu.

¶Karlsruhe Institute of Technology, Germany and University of Tübingen, Germany, Email: thimme@kit.edu.

‖Karlsruhe Institute of Technology, Germany and Georg-August-University Göttingen, Germany, Email: uhrig@kit.edu.

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 (e.g. see Chen and Zimmermann (2021) and 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 by Fama and French (1993) and its various extensions. Within the finance literature, these patterns are commonly referred to as *anomalies*. However, it is not clear which of these patterns are due to differences in systematic risk exposures across portfolios and which are due to mispricing. We designate the former as *consensual anomalies*, alluding to a consensus among market participants to refrain from trading against disparities in prices corresponding to cross-sectional variation in discount rates. In contrast, we term the latter type *mispricing anomalies*, representing anomalies in the true sense, wherein we assume the existence of market participants desiring to trade against them but facing frictions impeding their actions.

Persistent mispricing leads to significant misallocations of capital in the real economy. Binsbergen and Opp (2019) argue that these misallocations lead to distorted investment policies of overvalued or undervalued firms, and that there would be substantial economic efficiency gains if these mispricings would be eliminated. It is therefore of crucial importance to first identify which patterns in the cross-section of expected returns are mispricing anomalies and then understand why financial market participants do not trade sufficiently against the associated mispricings to profit from them and, at the same time, mitigate them.

To tackle the first problem, we make use of the fact that profit-seeking informed investors realize that mispricings constitute investment opportunities. Easley et al. (1998) show that it can be optimal for these investors to trade in the options market rather than the equity market. More specifically, informed investors can either buy (sell) a put option or sell (buy) a call option when perceiving a firm as overvalued (undervalued) and aiming to capitalize on the mispricing. Consequently, we expect to see larger option trading volumes for more mispriced stocks. If option volume was solely driven by hedging activities rather than also carrying information about speculation motives, we would not expect to see a volume-price link between option and equity markets. However, several papers show that option trading volume carries information about future stock prices (see Pan and Poteshman, 2006; Roll et al., 2010; Johnson and So, 2012; Ge et al., 2016).

Since options are in zero net supply, every buyer of a call option buys from a seller. In the absence of foreknowledge regarding the identity of informed investors, it is impossible to distinguish whether a buyer intends to trade against undervaluation or if a seller aims to trade against overvaluation. Thus, option trading volume can at best be informative about *absolute* mispricing, but not about the direction of the mispricing. Our key identifying idea is to combine information about option trading volume with anomaly signals: If an anomaly signal is informative about mispricing, the anomaly should be very pronounced among stocks with high option trading volume (and thus high absolute mispricing) and less pronounced among stocks with low trading volume (and thus low absolute mispricing).

In contrast, we do not expect informed investors to trade against consensual anomalies. Accordingly, if an anomaly signal is only informative about *consensual variation* in discount rates, such as variation in risk premia, it should be cross-sectionally orthogonal to the absolute mispricing signal comprised in option trading volume. In short, our argument implies that consensual anomalies should be evenly spread across stocks with high and low option trading volume while mispricing anomalies should be concentrated among stocks with high option trading volume.

To ascertain whether this theoretical argument is empirically reflected in stock data, we replicate 144 anomalies and examine long-short returns on the set of stocks with tradable options (details on the data are provided in Chapter 3). Of these anomalies, eleven are consistently categorized as mispricing-based in the papers by Chen et al. (2023) and Bali et al. (2023). Panel A of Table 1 displays long-short quintile returns averaged across these eleven anomalies. We find an unconditional return difference of 0.27% (t-statistic of 2.48) per month. Strikingly, conditioning on the amount of options trading in the underlying, we discover a monthly quintile long-short return of only 0.05% (t-statistic of 0.36) among stocks with low options trading volume, while they earn a monthly quintile long-short return of 0.66% (t-statistic of 4.67) among stocks with high options trading volume. The difference of 0.61% is highly significant with a t-statistic of 5.67. An example of an anomaly considered here is *momentum* (see Jegadeesh and Titman, 1993) for which we find an average long-short return of 1.11% on high option volume stocks. Among low option volume stocks, the momentum anomaly vanishes entirely (long-short returns of -0.01%).

Panel B of Table 1 shows results of the same exercise, but considers nine anomalies that are consistently categorized as "risk-based" (in Chen et al., 2023) and "other" (in Bali et al., 2023). These anomalies on average earn monthly quintile long-short returns of 0.22% (t-statistic of 2.18) on optionable stocks, which is close to the performance of mispricing anomalies considered above. However, the long-short return of 0.23% (t-statistic of 2.17) among stocks with low options trading volume is quite similar to the return of 0.28% (t-statistic of 2.11) among stocks with high options trading volume and the difference between these returns is statistically insignificant. An example of an anomaly in this category is the *investment* anomaly of Richardson et al. (2005), producing statistically significant long-short returns of 0.49% among stocks with high option trading volume and of 0.47% among stocks with low option trading volume.

Drawing from these insights, we introduce an analytical metric termed the *Option Volume Implied Mispricing Score* ($OVIMS$), assignable to each anomaly and naturally ranging between zero (consensual anomaly) and one (mispricing anomaly). It is constructed as the difference in long-short anomaly portfolio returns across option trading volume quintiles. More precisely, we perform 5×5 dependent double sorts on the option-to-stock volume (Roll et al., 2010, denoted O/S subsequently) and the candidate anomaly signal and consider the difference in anomaly return spreads across O/S quintiles. To ensure independence from the strength of the candidate anomaly, the resultant measure is normalized by the effect size, emphasizing a reliance solely on the extend the anomaly is related to mispricing.

We find that anomalies pertaining to the categories denoted as *momentum* and *profitability* consistently manifest as instances of mispricing anomalies, characterized by $OVIMS$ values hovering around 1. In contrast, signals emanating from the categories *investment*, *intangibles*, and *value* typically exhibit either negligible or statistically insignificant $OVIMS$ values. The most heterogeneous category is *frictions*. To give examples, eleven-month momentum and operating-profits-to-equity have $OVIMS$ of 1.01 and 1.06, respectively. Growth in book equity, R&D expenses, and the quarterly earnings-to-price ratio have $OVIMS$ of 0.03, 0.13, and -0.11, respectively. Examples within the *frictions* category include market equity and idiosyncratic volatility with $OVIMS$ of 1.05 and 0.91, but also systematic volatility and the Dimson beta with $OVIMS$ of 0.05 and -0.22.

But there is also variation within other categories: The annual book-to-market ratio has an $OVIMS$ of 0.5, statistically indistinguishable from 0 and 1. Consequently, the classic *value* does not distinctly align itself with either consensual or mispricing anomaly types. When considering all individual anomalies that we use in our analysis, we find that $OVIMS$ is positively related to the strategy's alpha and other mispricing classifications that have been recently put forward in the literature (Bali et al., 2023; Chen et al., 2023; Frey, 2023).

In substantiating the validity of our baseline assumption positing that informed investors employ options as instruments for capitalizing on stock mispricings, we analyze prices of options vis-a-vis prices of the underlying stocks. In an ideal scenario where market makers impeccably hedge their option positions, an increased demand for specific options would seamlessly translate into commensurate price pressure in the stock market. However, Garleanu et al. (2009) point towards challenges faced by market makers in effectively hedging their option positions during periods of elevated option demand. Consequently, the mid prices of options may escalate during periods of high demand, even surpassing levels anticipated by put-call parity. To systematically explore these dynamics, we construct synthetic stock positions using at-the-money call and put options written on single stocks. By assessing the price discrepancies between synthetic and actual stock positions, we derive insights about the directional trading tendencies of option end users.

For anomalies with high $OVIMS$, i.e., those categorized as mispricing anomalies, our analysis reveals that option-implied synthetic stock positions within the anomaly short portfolio are, on average, cheaper than the corresponding stocks themselves, and vice versa for the long portfolio. These price deviations between stock and options markets strongly suggest that option traders increasingly buy puts or sell calls of stocks included in the short portfolio, and vice versa for the long portfolio. Stated more explicitly, option traders actively trade against the direction of the stock mispricing and the resultant demand-driven price pressure on options palpably mitigates the extend of the anomaly in the options market. As an example, returns on long-short portfolios sorted by idiosyncratic volatility amount to 0.83% with (physical) stocks, but only 0.72% with synthetic stocks. The difference of eleven basis points is not only statistically significant, as indicated by a t-statistic of 4.26, but also holds economic significance, considering that arbitrage forces should cause option prices to align with stock prices.

Conversely, we find no evidence for directional trading demand in case of the majority of consensual anomalies. Illustratively, the *investment* anomaly *change in book value* yields long-short returns of 0.26% with both stocks and options. This observation holds true even when we restrict our analysis to stocks with high option trading volume, a measure that greatly amplifies the stock-option spread for most mispricing anomalies.

Our findings prompt two follow-up questions: Who are those informed investors trading against mispricings at the options market, and does their trading activity exhibit systematic temporal variations? To answer the first question, we study agent-specific measures of option order imbalance to quantify each agent's net position (long or short) in a given stock. Our analysis yields empirical support, indicating that proprietary traders build option positions to trade against mispricings and, by that, serve as the primary catalyst of the observed price wedges between stocks and option-implied synthetic stock positions. This is true for mispricing anomalies such as momentum and idiosyncratic volatility. Our finding is consistent with the notion of informed investors being professionals in financial institutions with large research departments, equipped with the capability to identify mispriced stocks. In line with that Beckmeyer et al. (2023) find that proprietary traders heavily trade options to get exposure to option momentum strategies.

To answer the second question, we start with the premise that informed investors are particularly motivated to trade against mispricing when it is very pronounced. In such periods, we expect large spreads between option-implied synthetic and actual stock prices. We investigate whether these spreads are more substantial during periods characterized by elevated financial market frictions. Specifically, we conduct regressions of anomaly-specific stock-option spreads against metrics quantifying the extend of short-sale constraints, stock liquidity, option liquidity, funding constraints, and intermediary capital constraints.

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. (2023b) 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. While we do not discount the influence of borrowing fees, we also consider other frictions, and in our analysis, it could be a possible outcome that stock borrow fees explain the entire variation. Indeed, in our analysis, we find a strong influence of short-sale constraints on all mispricing anomalies. However, we also observe an impact of stock liquidity, especially on frictions-based and value-based mispricing anomalies, and an impact of intermediary capital frictions and funding frictions on profitability-based mispricing anomalies.

The latter observation holds notable policy implications: Our results indicate that substantive real inefficiencies arising from capital misallocation primarily emanate from the magnitude of trading costs, manifesting as high short selling costs and low stock liquidity during periods wherein trading has the potential to rectify prices. Notably, short-selling costs appear to impede a more effective correction of overvalued firms. Additionally, our results suggest that improving funding liquidity and mitigating frictions in the financial intermediary sector also emerges as a factor in the endeavor to enhance the efficiency of market mechanisms for capital allocation.

Our paper proceeds as follows. Section 2 presents a theoretical framework elucidating the fundamental rationale underlying our mispricing score. In Section 3 the empirical analysis of this measure is conducted, classifying anomalies as mispricing- or consensual-based. Section 4 evaluates anomaly portfolio returns derived from synthetic stock positions, drawing comparisons with stock anomaly portfolio returns, and explores the relation with the previously discussed mispricing score. In Section 5, we examine option order imbalance among various trader types, affirming the active engagement of proprietary traders in trading against specific mispricing anomalies. Section 6 establishes the relation of the stock-option difference in anomaly returns with several friction measures, before Section 7 concludes.

Related literature The paper by Binsbergen and Opp (2019) emphasized the importance of working out which anomalies are mispricing-based. Frey (2023) develops a measure based on analyst predictions. Although his method is completely different from our approach, he finds largely consistent results: Anomalies from the momentum and profitability categories are predominantly identified as mispricing-based in his paper. Bali et al. (2023) measure firm-level mispricing as the deviation of the firm's return from the fair rate of return implied by an IPCA model. They also aggregate their results to an anomaly portfolio level and find that many momentum, profitability and friction-based anomalies are mispricing-based. Chen et al. (2023) classify an anomaly as either mispricing- or risk-based depending on the original authors' statements. As suggested by the motivating example in the introduction, our score is strongly positively related to these measures, as discussed in detail in Section 3.3.

Frey (2023) and Bali et al. (2023) make a reference to the concept of build-up vs. resolution anomalies established by van Binsbergen et al. (2023). This involves looking at the long-term performance of anomaly portfolios and finding medium- to long-term return reversals. Our paper focuses on the one-month horizon and shows that option traders mainly seek exposure to stocks associated with build-up anomalies. We compare our score with theirs in Section 3.3.

Our paper contributes to a large body of literature suggesting that option trading volume is informative about the underlying's stock price. Early contributions to this field were made by Easley et al. (1998) and Pan and Poteshman (2006), who show that option volume, once conditioning on the direction of option trades, provides information about the future stock price of the underlying. Roll et al. (2010) find that total option-to-stock volume positively predicts announcement returns around earnings announcements, implying that informed investors use options to maximize the economic gains from their information. Johnson and So (2012) look at the entire cross-section of (optionable) stocks and find that option-to-stock volume negatively predicts stock returns in the subsequent period. They argue that option traders primarily trade on negative news and use options as a tool to avoid costly short selling in the stock market. Ge et al. (2016) decompose option volume into open/close buy and open/close sell volumes and find that the volume related to the purchases of calls that open new positions is the strongest return predicting component of option-to-stock volume. They highlight the role of options in providing embedded leverage to informed investors seeking to maximize profits.

We also contribute to the literature examining the impact of frictions on asset prices. The literature has shown that stocks with high short selling fees earn lower returns on average. Besides single stock returns, short selling fees are also an important ingredient in understanding anomaly portfolio returns in particular (see e.g. Muravyev et al. (2023a); Muravyev et al. (2023b); Drechsler and Drechsler (2021)). Other studies highlight the role of market liquidity in understanding asset prices. Amihud and Mendelson (1986) consider the relation between a stock's market liquidity and expected returns. They find a positive liquidity premium in the sense that stocks with high bid-ask spreads have higher returns on average. This relation has been confirmed in numerous subsequent studies.

Liquidity constraints can also impact option prices. Engle and Neri (2010) show that high hedging costs for an option lead to lower option liquidity. This suggests that option liquidity should also be an important determinant for option prices. Christoffersen et al. (2018) provide empirical support for this claim and find that illiquid options have higher returns than liquid ones. However, Duarte et al. (2023) show that their findings are contaminated by look-ahead bias and, consistent with that, we do not find a strong impact of option liquidity on the wedge between synthetic and physical stock prices either.

Recently, a growing body of literature suggests that financial intermediaries are marginal in many asset classes (see e.g. Haddad and Muir (2021); He et al. (2017); Adrian et al. (2014)). The literature shows that intermediary frictions are an important ingredient in understanding the cross-sectional and time series variation in asset returns. Our analysis reconsiders this channel, controlling for other types of frictions. We find that financial intermediary frictions primarily impact the magnitude of anomalies from the profitability category.

2 Mispricing and option trading activity

2.1 A stylized framework

This section provides a framework for a structured analysis of the relation between option trading volume and anomaly returns. We consider a one-period model with points in time denoted by t and $t+1$ and stocks $i = 1, \ldots, I$. We assume that stocks can be mispriced, meaning that there can be a wedge between the fundamental value $V_{i,t}$ of stock i and the price $P_{i,t}$ for which the stock can be traded. The difference between value and price is given by

$$M_{i,t} = V_{i,t} - P_{i,t} = \sigma^M \varepsilon^M_{i,t} \tag{1}$$

where $\varepsilon^M_{i,t} \sim N(0,1)$ and σ^M quantifies the cross-sectional variation in mispricing. The fact that the cross-sectional average mispricing is equal to zero is for simplicity but not crucial for the following arguments.

At time $t+1$ all firms are liquidated, so that $V_{i,t+1} = P_{i,t+1}$. We assume that the value of stock i evolves as

$$V_{i,t+1} = V_{i,t} + RP_{i,t} + \sigma^P_i \varepsilon^P_{i,t+1} \tag{2}$$

where σ^P_i denotes the (time series) volatility in the value of stock i. $RP_{i,t}$ denotes a risk premium and could be more explicitly related to σ^P_i, but, as it is not crucial for our framework, we simply define $RP_{i,t} = \mu^{RP} + \sigma^{RP}\varepsilon^{RP}_{i,t}$. The shocks $\varepsilon^P_{i,t+1}$ and $\varepsilon^{RP}_{i,t}$ are i.i.d. $N(0,1)$-distributed and independent from $\varepsilon^M_{i,t}$. Although our framework allows for other scenarios, we will assume that $\sigma^M > 0$ and $\sigma^{RP} > 0$, implying that there is cross-sectional variation in *expected returns*, which is due to both, variation in mispricing *and* variation in risk premia.

We can without loss of generality assume that $P_{i,t} = 1$ for all stocks i. The return on stock i can then be expressed as:

$$r_{i,t+1} = P_{i,t+1}/P_{i,t} - 1 = M_{i,t} + RP_{i,t} + \sigma^P_i \varepsilon^P_{i,t+1}$$

The goal of the *econometrician* is to quantify the part of $r_{i,t+1}$ that is in principle predictable, i.e., $M_{i,t}$ and $RP_{i,t}$. However, we assume that these two components are latent and the econometrician only observes a *characteristic* j, denoted $C_{j,i,t}$, which is an imperfect signal. More precisely, we assume that the cross-sectional distribution of characteristic j is given by

$$C_{j,i,t} = \mu_j + \sigma_j \left(\phi_j \left(\zeta_j \varepsilon^M_{i,t} + \sqrt{1-\zeta_j^2} \varepsilon^{RP}_{i,t} \right) + \sqrt{1-\phi_j^2} \varepsilon^C_{j,i,t} \right). \tag{3}$$

The cross-sectional mean and standard deviation of the characteristic j are given by μ_j and σ_j.[1] $\varepsilon^C_{j,i,t} \sim N(0,1)$ represents noise in the characteristic and can be correlated across characteristics (i.e., $\text{Cov}(\varepsilon^C_{j_1,i,t}, \varepsilon^C_{j_2,i,t}) \neq 0$ for two characteristics j_1 and j_2). ϕ_j is between zero and one and quantifies how informative the characteristic is about the predictable components in returns. Sorting stocks into portfolios yields an average return difference between high-C_j and low-C_j stocks if and only if ϕ_j is positive. The return difference is ceteris paribus increasing in ϕ_j.

ζ_j is the parameter that is central to the analysis of our paper. It also lies between zero and one and expresses the extent to which the characteristic j is informative for the mispricing component relative to the risk premium component. A characteristic with $\zeta_j = 0$ only captures cross-sectional variation in risk premia but is not informative about mispricing. In contrast, a characteristic with $\zeta_j = 1$ is only informative about the mispricing component. Characteristics with $0 < \zeta_j < 1$ are informative about both components.

Our goal is to estimate ζ_j for each characteristic to quantify if it is rather a mispricing or a consensual anomaly. For that purpose, we consider an alternative signal that is the trading behavior of sophisticated agents. Different from the econometrician who only observes characteristics as signals, we assume that sophisticated agents have private information about the mispricing component in prices at time t. We assume that they observe a signal

$$S_{i,t} = V_{i,t} + \sigma^S \varepsilon^S_{i,t}, \tag{4}$$

where $\varepsilon^S_{i,t}$ represents noise in the private signal. It is i.i.d. $N(0,1)$-distributed and independent of all other shocks. $S_{i,t}$ can be thought of as an analyst report about the true value of a stock.

[1]We can w.l.o.g. assume that $\mu_j = 0$ and $\sigma_j = 1$.

In line with Easley et al. (1998), we assume that sophisticated agents trade in the option market when they believe a stock is mispriced. The option trading volume $OTV_{i,t}$ in options of the underlying i at time t is assumed to be

$$OTV_{i,t} = |S_{i,t} - P_{i,t}| = |M_{i,t} + \sigma^S \varepsilon^S_{i,t}|.$$

The equation implies that sophisticated traders take larger option positions if their signal indicates a stronger mispricing. Here, we do not look at signed option order imbalance, indicating whether the sophisticated agents believe stock i is under- or overvalued. The reason is that options are in zero net supply and, at this point, we do not want to take a stand on who is sophisticated and consider a particular party's effective long or short positions.

Importantly, sophisticated traders only trade against the mispricing component, but not against the risk premium component. The reason is that they agree with all other market participants in that the risk premium component is a fair compensation for taking the risk of holding a long position in a stock.

2.2 Implications

We evaluate the framework quantitatively and assume the following parameters: There are $I = 4{,}000$ stocks in the cross-section and the average risk premium is $\mu^{RP} = 0.01$, corresponding to a monthly window. We assume that the predictable part in returns is split evenly into the mispricing component and the risk premium component with $\sigma^M = \sigma^{RP} = 0.01$. Unpredictable noise in returns amounts to $\sigma_P = 0.1$ and we consider the cases of a perfect signal ($\sigma^S = 0$) and a noisy signal ($\sigma^S = 0.5$).

We consider informative but noisy characteristics with $\phi_j = 0.2$ and let ζ_j range between 0 and 1. We draw 30,000 samples of returns and characteristics and split them into 100 chunks of 300 observations. We perform dependent double sorts of the 4,000 stocks into 5×5 portfolios: We first sort on OTV and then, within each OTV-quintile, on the simulated characteristic. Table 2 shows average returns on the 25 portfolios for the two cases where the characteristic is either only informative about the mispricing component ($\zeta_j = 1$) or the risk premium component ($\zeta_j = 0$), and the two cases where the signal is perfect ($\sigma^S = 0$, Panel A) or noisy ($\sigma^S = 0.5$, Panel B).

Panel A shows that the return difference between high- and low-characteristic stocks is increasing in option trading volume. The low option trading volume quintile only contains stocks for which the absolute mispricing component is small, so that sorting on a characteristic that is only informative about mispricing ($\zeta_j = 1$) does not yield large return spreads. If the characteristic is not informative about the mispricing component ($\zeta_j = 0$), but only about the risk premium component, the size of the return spreads are completely unrelated to option trading volume. This is because the sophisticated traders do not trade on the risk premium component.

When the signal is noisy (Panel B), the patterns are very similar. Importantly, the return spread between high- and low-characteristic stocks is of similar magnitude when the characteristic is only informative about the risk premium component ($\zeta_j = 0$). When the characteristic is informative about the mispricing component ($\zeta_j = 1$), there is now also a sizable return spread in the low option trading volume quintile. This is because the characteristic contains additional information about the mispricing component relative to the private signal. Still, the spread within the high option trading volume quintile portfolio is much larger.

The findings in Table 2 suggest a relation between ζ_j and the difference between the return spread within high option trading volume stocks and the return spread within low option trading volume stocks. To be independent of the total strength of the anomaly (quantified by ϕ_j), we normalize this difference by the maximum spread across option trading volume quintiles and define

$$OVIMS_j = \frac{(R_{\text{high OTV,high } C_j} - R_{\text{high OTV,low } C_j}) \ - \ (R_{\text{low OTV,high } C_j} - R_{\text{low OTV,low } C_j})}{\max_k (R_{\text{OTV}_k,\text{high } C_j} - R_{\text{OTV}_k,\text{low } C_j})}. \quad (5)$$

Here, $R_{\text{high OTV,high } C_j}$ denotes the average return on stocks in the high OTV and high characteristic portfolio and similarly for the other returns. Coming back to the special cases shown in Table 2, $OVIMS_j$ is distinctly positive when $\zeta_j = 1$, i.e., the characteristic is only informative about the mispricing component. In contrast, $OVIMS_j$ is close to 0 when $\zeta_j = 0$, i.e., the characteristic is only informative about the risk premium component.

Figure 1 shows $OVIMS_j$ as a function of ζ_j for the situations of a perfect and a noisy signal. $OVIMS_j$ increases monotonically with ζ_j and lies between 0 and 1 when the signal is perfect. The functional form is slightly S-shaped. The shape is retained if the signal is noisy, but then $OVIMS_j$ only ranges from 0 to, in this case, 0.75. Importantly, since the amount of noise in the private signal is not specific to any characteristic, we can use $OVIMS_j$ to compare different characteristics in terms of their informativeness about the mispricing component relative to the consensual component.

3 Mispricing score

In this chapter, we empirically construct the Option Volume Implied Mispricing Score ($OVIMS$) for each anomaly that we consider in our analysis. Subsequently, we classify anomalies into mispricing and consensual types. Our theoretical framework posits that option traders actively seek exposure to mispriced stocks, viewing them as lucrative investment opportunities. Consequently, we anticipate that anomalies indicative of mispricing will yield particularly pronounced long-short returns within stocks characterized by high volumes of options trading. In contrast, in cases where an anomaly is indicative of consensual variations in discount rates, we do not anticipate discernible return differences between stocks with high option trading volumes and those with low option trading volumes.

3.1 Data

In our empirical analyses, we adopt the option-to-stock volume (O/S) metric, as introduced by Roll et al. (2010), as a readily available measure to quantify the extent of options trading activity of sophisticated investors. O/S of a stock is given as the total trading volume in option contracts written on the stock, irrespective of moneyness or maturity, within the considered month, divided by the corresponding stock trading volume in shares. We obtain options data from the OptionMetrics Ivy DB database.

Bondarenko and Muravyev (2023) show that out-of-the-money (OTM) options are more informative about future stock returns than at- or in-the-money options, likely since they are more attractive for speculators due to the fact that they provide higher embedded leverage. As a robustness test, we also conduct the following analysis with a version of the option-to-stock volume that only considers trading volumes of OTM options (defined as options with absolute deltas below 0.375). The findings are very similar to those shown here and presented in Table A5 of the appendix.

Our analysis is conducted on a cross-section of common stocks, actively traded at NYSE, AMEX, or Nasdaq. As it is common in the anomalies literature, we exclude financial companies and companies with negative book equity. In our later analysis, we compare stock prices with option-implied prices of the underlying, using put-call parity (see Section 4). Thus, we reduce our sample further to have a consistent data set across all analyses. We only consider stocks that have options with standard settlement and expiration dates and apply a number of filters concerning the properties of the options, following Goyal and Saretto (2009). In particular, we exclude observations where the option price violates standard arbitrage bounds: Options with an ask price lower than the bid price, a bid price of zero, and with a bid-ask spread lower than the minimum tick size. In addition, we delete observations where the open interest is equal to zero. Since our later analysis stems from put-call parity (see Section 4), we control for the possibility of early exercise by excluding stock months with dividend payments and observations where the time value is less than 5% of the option price.

We consider holding periods between two standard maturity dates (usually the third Friday of a month). At the first trading day of the holding period, we pick the call-put pair closest to at-the-money (ATM) and expiring in the next month. We do this for each stock in each month, so that our sample consists of only stocks that have ATM call-put pairs with one month to maturity. Note that we calculate monthly stock returns for those firms over the same one month to maturity. Our final sample spans from March 1996 through December 2018 and consists of an average of 979 stocks per month.

We replicate a total of 144 anomalies, following the information provided by Hou et al.

(2020), and use their categorization of anomalies into the six categories momentum, profitability, frictions, value, investment, and intangibles. Appendix A1 provides a detailed description of the anomalies used in our analysis (see Table A1) and data pertaining to the replication performance (see Figure A1). Importantly, our restricted sample is much smaller with respect to the time-series and the cross-sectional dimension than the samples used in other studies, such as Hou et al. (2020). While some anomalies are more pronounced, many are less pronounced on the subsample of optionable stocks between 1996 and 2018. Böll et al. (2023) carefully analyze the difference between the two samples and find that optionable stocks are on average more liquid and have a higher market capitalization. After controlling for these differences anomalies are on average as pronounced on optionable than on non-optionable stocks.

3.2 Mispricing scores of anomalies

We exemplify our mispricing score using three popular anomaly signals: a momentum anomaly ($Releven$ - returns over the past twelve months, skipping the most recent month), a friction anomaly ($Ivol\_FF3$ - idiosyncratic volatility relative to the 3-factor model), and an investment anomaly (dBE - annual change in book equity). Specifically, we initially sort stocks into five portfolios based on their option-to-stock volume and subsequently, within each O/S quintile, further sort stocks into five portfolios based on the respective characteristic. All variables that we use for sorting are lagged by one month in order to avoid any look-ahead bias. The results are presented in Table 3.

We observe a predominantly monotonic increase in long-short returns across the O/S quintiles for both the momentum and idiosyncratic volatility anomalies. For instance, the momentum return registers at -0.01% (with a t-statistic of -0.02) per month for stocks in the lowest O/S quintile. In contrast, for stocks in the highest O/S quintile, the momentum return significantly escalates to 1.11% (with a t-statistic of 2.79) per month. The resulting monthly difference of 1.12% is statistically significant, underscored by a t-statistic of 3.70. Qualitatively similar results are observed for the idiosyncratic volatility anomaly.

In contrast, a distinct pattern emerges for the investment anomaly. The long-short return stands at 0.47% (with a t-statistic of 2.52) in the lowest O/S quintile and 0.49% (with a t-statistic of 1.93) in the highest O/S quintile, with the difference between the two being statistically indistinguishable from zero. In light of our rationale, we categorize momentum and idiosyncratic volatility as indicative of mispricing, while the annual change in book equity is considered more informative about consensual variations in discount rates.

Drawing from these findings, we construct the Option Volume Implied Mispricing Score ($OVIMS$) for all anomalies under consideration in our analysis, according to Equation (5). The $OVIMS$ of the three considered anomalies are 1.01 for $Releven$, 0.91 for $Ivol\_FF3$, and 0.03 for dBE. Note that $OVIMS$ may assume values exceeding 1 if the long-short returns within stocks with low option trading volume exhibit negative values. Similarly, $OVIMS$ can be negative if the long-short returns are larger within stocks with low option trading volume, relative to those with high volume.

Table 4 presents $OVIMS$, together with standard errors, t-statistics, and bootstrapped 95%-confidence intervals for all 144 anomalies.[2] 38 of them exhibit a significantly positive $OVIMS$. Notably, anomalies within the profitability, momentum, and friction categories are frequently among those with large and significant $OVIMS$. Specifically, 12 out of the 16 profitability anomalies show significantly positive $OVIMS$ (5 out of 9 for momentum and 11 out of 25 for frictions). Among friction anomalies, those related to return volatility, size, and liquidity particularly stand out.

These findings suggest that anomalies associated with the momentum, profitability, and frictions categories are particularly informative about stock mispricings. Further anomalies pertaining to these categories do not show significantly positive $OVIMS$ at the 5% significance level, but the point estimates are still large, suggesting that these anomalies are also to be interpreted as mispricing rather than consensual anomalies. Examples are SUE (standardized unexpected earnings - a momentum anomaly) with an $OVIMS$ of 1.35, $CVDtv$ (coefficient of variation for dollar trading volume - a frictions anomaly) with an $OVIMS$ of

[2]The t-statistics reported in Table 4 are computed by taking the effect size in the definition of $OVIMS$ as given. Thus, they neglect the sampling variation in the maximum long-short return across O/S quintiles. The bootstrapped confidence intervals also control for this sampling variation. We find that doing so does not influence the results materially, since the sampling variation in the effect size in the denominator of the definition of $OVIMS$ is strongly correlated with the spread in long-short returns in its enumerator.

0.97, and Opa (Operating profitability-to-assets) with an $OVIMS$ of 0.64.

Conversely, we observe less pronounced results for anomalies within the value, investment, and intangibles categories. Only 4 of the 25 value anomalies display positive and significant $OVIMS$ (3 out of 38 in the intangibles category and 3 out of 31 in the investment category). In contrast, we find that 11 out of 25 value anomalies are significantly smaller than 1 (11 out of 38 for intangibles and 10 out of 31 for investment), suggesting that these anomalies rather provide information about consensual variations in discount rates, rather than mispricing.

However, the picture is colorful, rather than just black and white. Many anomalies have $OVIMS$'s between 0 and 1. For example, the annual book-to-market ratio BMa - a classic value anomaly - has an $OVIMS$ of 0.5, and the confidence interval includes 0 and 1. Thus, our measure can neither clearly rule out a risk-based rationale (as advocated by, e.g., Kogan and Papanikolaou (2014) and Donangelo (2021)), nor a mispricing-based rationale (as advocated by, e.g., Daniel et al. (2001) and Ali et al. (2003)).

Moreover, as $OVIMS$ is a return-based measure and can only be calculated on a relatively short sample, it is naturally estimated with substantial estimation error. It is thus instructive to consider average $OVIMS$ across anomalies in the different categories. The average $OVIMS$ of momentum and profitability anomalies are both equal to 0.88, in line with our earlier assessment that these anomalies are rather mispricing anomalies. Value, investment, and intangibles anomalies have average $OVIMS$ of 0.21, 0.22, and 0.20, respectively and can thus, on average, be considered consensual. Friction anomalies have an $OVIMS$ of on average 0.57 with a lot of variation across anomalies. Friction-based anomalies can vary greatly in their nature and should therefore not be seen as a uniform category. As a result, it is also not possible to clearly label them as mispricing or consensual anomalies.

3.3 Relation with other mispricing scores

In this section, we compare $OVIMS$ with other mispricing scores. The most popular and most commonly used score in the literature is a strategy's alpha, relative to a factor model. Under the assumption that the used 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 an anomaly's $OVIMS$ to its unconditional, full sample alpha relative to the CAPM, the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, and the Hou et al. (2015) q-factor model. To ensure consistency between the timing of anomaly portfolio returns and factor returns, we manually calculate factor returns from option maturity to option maturity. To this end, we use daily portfolio returns from the data libraries of Kenneth R. French and Hou-Xue-Zhang. Following, we use the quintile long-short returns of anomalies and compute unconditional, full sample alphas spanning from March, 1996 to December, 2018. We plot an anomaly's alpha against its $OVIMS$ and fit a linear model. Figure 2 shows the results.

We find positive relationships between the anomalys' unconditional alphas and their $OVIMS$ across all four factor models. This means that on average high $OVIMS$ anomalies have higher unconditional alphas than low $OVIMS$ anomalies. There is some variation especially for some of the high $OVIMS$ anomalies showing negligible alpha. This is not surprising as we consider a sample of optionable stocks which might influence the effect size of certain anomalies. Also, many asset pricing models such as the three-factor, five-factor and q-factor model precisely account for the variation in returns that is produced by many high $OVIMS$ anomalies pertaining to the profitability or friction category.

We also compare $OVIMS$ with other mispricing measures that have been recently put forward in the literature. Firstly, we consider the mispricing measure introduced by Bali et al. (2023, hereafter referred to as BBW), which assesses mispricing as the deviation of a firm's return from the fair rate of return implied by an IPCA model. They also aggregate their results to an anomaly portfolio level which we use for our comparison. Similarly, we examine the mispricing classification by Chen et al. (2023, hereafter referred to as CLZ), which categorizes anomalies as either mispricing- or risk-based, depending on the statements of the authors of the original papers. Additionally, we consider the mispricing measure presented by Frey (2023, hereafter referred to as $Frey$), which employs earnings forecasts to link anomalies to biased expectations and mispricing. Lastly, we use the measure introduced by van Binsbergen et al. (2023, hereafter referred to as $BBOT$), which categorizes anomalies into types exacerbating or resolving mispricing.

To overcome the challenge that every study uses its own subset of anomalies, we manually match anomalies and their mispricing measures to those that are used in our study. We successfully match 110 anomalies from BBW to those in our analysis (94 from CLZ, 82 from $Frey$ and 30 from $BBOT$). We exclude another 30 matched anomalies from CLZ where the authors were agnostic and could not assign an anomaly into mispricing- or risk-based classifications, effectively leaving 64 matched anomalies pertaining to the two categories. Out of the 110 matched anomalies from BBW, 41 anomalies are classified as mispricing-based by the authors (47 for CLZ and 37 for $Frey$).

For BBW, CLZ, and $Frey$, we create a dummy variable indicating whether the authors classify the anomaly as mispricing-based. For $BBOT$, we report the price wedges, as the categorization of anomalies into types exacerbating (corresponding to a positive wedge) or resolving (corresponding to a negative wedge) mispricing differs from the other three scores. Subsequently, for every matched anomaly, we plot the mispricing dummies of the anomalies against their OVIMS. We also fit a logistic model, with the fitted value indicating the probability of an anomaly being classified as mispricing-based by the respective authors, given its OVIMS. For $BBOT$, we fit a linear model as the dependent variable is not binary. Figure 3 shows the results.

We find that classification via $OVIMS$ leads to results that are largely consistent with other mispricing classifications. High $OVIMS$ anomalies exhibit a higher probability to be classified as mispricing-based by BBW, CLZ and $Frey$ in comparison to low $OVIMS$ anomalies. Noteworthy is the alignment with BBW, where low $OVIMS$ anomalies exhibit a near-zero probability of being classified as mispricing-based, while those with high OVIMS values demonstrate a probability approaching 75%. The probability that a high-$OVIMS$ anomaly is classified as mispricing in the original article is also 75%, as indicated by the CLZ graph. However, for low-$OVIMS$ anomalies this value exhibit 50%, indicating that the authors of the original articles explain their findings by a mispricing channel more frequently than BBW (who use a rather sophisticated factor model).

In the case of Frey (2023), we find the lowest probability, around 60%, for high $OVIMS$ anomalies to be classified as mispricing-based. One reason for this result is the fact that many *high* $OVIMS$ anomalies pertaining to the friction category such as Dtv (dollar trading volume), STR (short-term reversal), ME_June (size), Ami (illiquidity) or PPS (price) amongst others are classified as "other", i.e. not mispricing-based, by Frey (2023).

Lastly, we find a tendency for low $OVIMS$ anomalies to resolve mispricing in the spirit of van Binsbergen et al. (2023) while high $OVIMS$ anomalies tend to do less so. This is not surprising, since van Binsbergen et al. (2023) find that especially profitability and momentum-based anomalies exacerbate mispricing instead of resolving it. Our findings show that those anomalies exhibit consistently high $OVIMS$. At the same time, risk-based anomalies may appear as resolution anomalies if the corresponding risk factor is not accounted for in the asset pricing model. This is consistent with low-$OVIMS$ anomalies exhibiting strongly negative price wedges.

4 Demand-based option pricing

The baseline assumption behind our mispricing score is that informed traders recognize stock mispricings and use the options market to trade against them. The definition of $OVIMS$ rests on the assumption that option trading volume is indicative of informed trading, but it does not take the direction of the option trades into account. However, if our assumptions are correct, informed traders will build option positions with positive exposures to undervalued stocks, i.e., buy calls or write puts. Conversely, they buy puts or write calls if they perceive a stock as overvalued.

Garleanu et al. (2009) show that option dealers cannot hedge their positions perfectly due to 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 the demand-based option pricing theory, increased buying pressure for calls and selling pressure for puts, resulting from an underpriced stock, lead to higher call prices and lower put prices. In this case, acquiring a synthetic long stock position (an options position with a delta of one) is thus more expensive than buying the underpriced stock position itself. The option position can still be the better choice for the informed trader due to the built-in leverage and potential other frictions in the stock market. Importantly, if informed traders heavily trade in options of underpriced stocks, the option positions replicating these stocks should increase in price, meaning that the synthetic stock positions are less underpriced than the stocks itself. The exact opposite should hold for overpriced stocks.

4.1 Empirical approach and data

To analyze this potential channel empirically, we consider a model-free decomposition of the excess return r_S^e on a stock S into the return r_F on a synthetic forward F, consisting of a long-call and a short-put position, and the excess return r_G^e on a so-called *conversion trade*:

$$\begin{aligned} r_S^e &= \frac{S_T - S_0}{S_0} - r_{0,T} \\ &= \frac{F_T - F_0 + (S_T - F_T) - (S_0 - F_0)}{S_0} - r_{0,T} \\ &= \frac{F_T - F_0}{S_0} + \left(\frac{G_T - G_0}{S_0} - r_{0,T} \right) \\ &= r_F + r_G^e. \end{aligned} \tag{6}$$

Here, r_{t_1,t_2} denotes the risk-free interest rate between times t_1 and t_2 and $F_t = C_t - P_t$ is the price of a synthetic forward, with C_t (P_t) denoting the time-t price of a call (put) with strike X and maturity T. $G_t := S_t - C_t + P_t$ denotes the price of the conversion position, being long in the stock and short in the synthetic forward. Note that all returns are calculated relative to the stock price S_0 at initiation.

Why is Equation (6) an interesting decomposition? Ofek et al. (2004) define the *synthetic stock price* as

$$S_t^* := C_t - P_t + \frac{X}{1 + r_{t,T}}. \tag{7}$$

At maturity, the payout of this option position is S_T, so that $S_T^* = S_T$. Put-call parity implies that for non-dividend paying stocks, this equality also holds before maturity, i.e., $S_t^* = S_t$.

However, demand pressure may drive the price of the option position away from S.

For the special case of at-the-money-forward options, i.e., with $X = S_0(1 + r_{0,T})$, substituting Equation (7) in Equation (6) shows that the returns on the synthetic forward and the conversion have handy interpretations:

$$\begin{aligned} r_F &= \frac{S_T^* - S_0^*}{S_0} - r_{0,T} \\ r_G^e &= \frac{S_0^* - S_0}{S_0} \end{aligned} \tag{8}$$

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.

In the subsequent analysis, we consider for each stock in our sample the returns on the stock, the synthetic forward, and the conversion position. As before, we form quintile portfolios using the 144 firm characteristics discussed earlier as sorting criteria and consider equal weighted portfolio returns. We use the sample laid out in Section 3.1 and report returns between two maturity dates. Importantly, we hold all options until maturity, so that conversion returns are really given by price differences at the initiation of the trades.

In instances where a firm characteristic is informative about mispricing, a portfolio sort entails assigning undervalued stocks to the long portfolio, i.e. portfolio 5. If informed traders buy calls or sell puts to trade against this undervaluation, we expect the price pressure to drive the synthetic stock price up, relative to the price of the physical stock. This results in positive conversion excess returns for underpriced stocks. The opposite is true for overpriced stocks, i.e., we expect to see negative excess conversion returns for stocks in portfolio 1. In total, this implies that for any characteristic that is indicative of mispricing, we expect positive and large conversion long-short (i.e. portfolio 5 - portfolio 1) returns.

Contrarily, in cases where a firm characteristic is indicative of consensual variations in discount rates, we expect a lack of discernible evidence supporting directional trading demand from option traders. This infers that the conversion long-short returns associated with such anomalies should be statistically indistinguishable from zero.

4.2 Findings

Just as in Section 3.1, we first analyze returns on the momentum anomaly $Releven$, the frictions anomaly $Ivol\_FF3$, and the investment anomaly dBE and consider the remaining 141 characteristics afterwards. Returns on the according single-sorted quintile portfolios are presented in Table 5. For idiosyncratic volatility and momentum—both identified as mispricing anomalies according to the $OVIMS$ criterion—we observe monthly long-short returns of 0.83% (with a t-statistic of 1.88) and 0.49% (with a t-statistic of 1.19) on the stock market. In contrast, on the options market, the corresponding monthly long-short returns are 0.72% (with a t-statistic of 1.61) and 0.44% (with a t-statistic of 1.07). Notably, the differences between the two, quantified by conversion returns, are significantly positive at 0.11% (with a t-statistic of 4.26) and 0.04% (with a t-statistic of 3.17). These findings not only support our assumption that informed traders use options to trade against stock mispricings, but they also show that their trading activity can lead to a substantial reduction of anomaly returns.

The change in book value anomaly has an $OVIMS$ close to zero, so that we categorize it as a consensual anomaly. It can thus serve as a placebo test in the sense that we do not expect differences in conversion returns across quintile portfolios, since the directional option demand does not cross-sectionally line up with dBE. As expected, the long-short stock returns are equal to the long-short forward returns. Note that the forward returns are on average lower than the stock returns, which hints at the interest rate used to calculate excess returns to be inappropriate (we use the interest rate from OptionMetrics). In the case of long-short returns, the interest rate cancels out, so it is a good idea to interpret these and be careful when interpreting the individual portfolio returns.

If our hypothesized economic mechanism is truly at work, we would anticipate an amplification in conversion returns for mispricing anomalies when conditioning on the actual extent of options trading in the underlying stock. To investigate if this implication holds empirically, we conduct dependent double sorts on O/S and idiosyncratic volatility, momentum, and the change in book equity. Subsequently, we calculate portfolio conversion returns, and the results are presented in Table 6.

Consistent with our rationale, we observe substantial spreads in conversion returns for momentum and idiosyncratic volatility, particularly within the stocks belonging to the highest O/S quintile. Specifically, for momentum, the (long-short) conversion return stands at 0.00% (with a t-statistic of 0.23) per month for the bottom O/S quintile and 0.14% (with a t-statistic of 5.22) per month for the top O/S quintile. The significant difference of 0.14% (with a t-statistic of 4.25) per month underscores this pattern. Noteworthy variations between the lowest and highest O/S quintiles arise from recent losers, wherein the conversion return is 0.12% in the lowest O/S quintile and -0.08% in the highest O/S quintile. For idiosyncratic volatility, we observe qualitatively similar and even more pronounced outcomes.

Concerning the change in book value anomaly, Table 6 shows that there is no significant conversion return spread within any O/S quintile. This aligns with our arguments concerning consensual anomalies, suggesting that market participants do not wish to engage in active trading strategies against stocks linked to the returns of such anomalies.

Finally, we aim to examine the broader relationship between $OVIMS$ and conversion returns. Figure 4 illustrates the unconditional conversion returns of anomalies plotted against their non-normalized $OVIMS$. The corresponding numbers can be found in Table A2 in the appendix. Notably, we refrain from normalizing $OVIMS$ by the effect size in this context because conversion returns should not only be linked to the mispricing score, but also to the effect size of the anomaly. This is due to the absence of incentive to trade against an anomaly if there is no discernible effect in the first place. Consequently, we do not anticipate significant conversion returns under such circumstances.

Our observations indicate a general increase in conversion returns corresponding to an increase in non-normalized $OVIMS$ across anomaly signals. The figure illustrates that anomalies characterized by either a low $OVIMS$ or a small effect size exhibit conversion returns approaching zero. These very small conversion returns align with our expectation that investors refrain from utilizing options to trade against stocks influencing anomalous returns in instances where the anomaly is not indicative of mispricing or possesses a modest effect size. Conversely, when the anomaly is informative about mispricing and boasts a substantial effect size, informed investors appear to employ options to trade against the mispriced stocks, resulting in elevated conversion returns.

In alignment with our previous findings, we observe substantial conversion returns, particularly when conditioning on O/S, the volume of option trading in the underlying assets. We categorize anomalies into five groups based on their non-normalized $OVIMS$. Figure 5 shows, for each of these groups, the average non-normalized $OVIMS$ (horizontal axis) and the mean conversion long-short returns of the highest and lowest O/S quintiles (vertical axis).

The difference in conditional conversion long-short returns is proportionate to the non-normalized $OVIMS$, with conversion long-short returns being notably elevated among stocks exhibiting high O/S. This pattern is particularly pronounced for anomalies characterized by high $OVIMS$, i.e. mispricing anomalies. This empirical observation corroborates our assertion that informed investors utilize options to trade against the direction of stock mispricings. The resulting demand contributes to the emergence of a disparity between the stock price and the option-implied stock price, elucidated by the manifestation of conversion returns.

5 Identifying informed investors

Our empirical results prompt an investigation into the identification of informed investors that trade against stock mispricings at the options market. To achieve this, we develop agent-specific metrics of option order imbalance, quantifying each agent's net position (long or short) in a given stock. These measures are then related to conversion returns associated with mispricing anomalies. We deliberately zoom in on mispricing anomalies in the subsequent chapters, as in general, mispricing anomalies show economically large and statistically significant conversion returns (as shown in Chapter 4). By doing so, we aim to discover which agents' demand is influencing the option-implied stock price, deviating it from the observed stock price for the stocks driving anomalous returns of mispricing anomalies.

5.1 Empirical approach and data

We utilize open-close data sourced from the International Securities Exchange (ISE). This dataset encompasses details regarding open/close buy and sell transactions executed by various agents, including customers, professional customers, firm broker-dealers, and firm proprietary traders, for each option associated with a given stock. The market maker position is inferred indirectly by presuming that they act as the counterparty to either customer or firm trades. The dataset's temporal coverage starts in May 2005, thereby establishing our sample period from May 2005 to December 2018.

One limitation of our analysis in this chapter is that trading on the ISE only covers less than half of of the total options trading on individual stocks (see Ge et al., 2016; Grauer et al., 2023). For this reason, we do not use the directional options trading data employed here for defining our mispricing scores in Chapter 3. The options trading volume from OptionMetrics, compared to the data used here, encompasses the entire market and is therefore better suited for defining $OVIMS$. Nevertheless, if traders engaging in trading against mispricing anomalies also do so via the ISE, we still hope to gain insights into their identity from the approximate measure used here.

We aggregate buy and sell volumes pertaining to each specific option and each type of trader. Our analyses employ a delta-adjusted option order imbalance metric, necessitating the extraction of an option's delta from OptionMetrics. We then consolidate the delta-adjusted buy and sell volumes at the stock-day level. Finally, we compute the option order imbalance metric for a given stock (s), agent (j), and day (t):

$$OI_{s,j,t} = \frac{CallBuy_{s,j,t} + PutSell_{s,j,t} - CallSell_{s,j,t} - PutBuy_{s,j,t}}{CallBuy_{s,t} + PutSell_{s,t} + CallSell_{s,t} + PutBuy_{s,t}} \tag{9}$$

where

$$CallBuy_{s,j,t} = \sum_{calls\ c\ on\ s} |\Delta_{c,t}| \cdot VolBuy_{c,j,t} \tag{10}$$

and

$$CallBuy_{s,t} = \sum_{j} CallBuy_{s,j,t} \tag{11}$$

and likewise for the other positions. Here, $VolBuy_{c,j,t}$ denotes the volume of trader type j in option c on day t.

The $OI_{s,j,t}$ metric is normalized within the range of -0.5 to 0.5. A value of $OI_{s,j,t} = 0$ indicates that agent j has not altered their inventory, maintaining a net exposure to the underlying stock s consistent with the previous day. A positive value of $OI_{s,j,t}$ signifies that agent j has adjusted their inventory to acquire a more positive exposure to the underlying stock on day t, while a negative value indicates that agent j has modified their inventory to attain a more negative exposure to the underlying stock relative to the previous trading day.

One day prior to the formation of the conversion portfolio, we aggregate the agent's $OI_{s,j,t}$ values over the preceding month for each stock, investigating whether an agent accumulates an inventory that results in a net exposure to the underlying stock. Subsequently, for each mispricing anomaly, we calculate the equally weighted average of the aggregated $OI_{s,j,t}$ values for stocks within portfolio 5 and portfolio 1. We compute a *long-short option order imbalance* ($LSOI$) measure for each mispricing anomaly a, trader type j, and month t as follows:

$$LSOI_{a,j,t} = \frac{1}{n} \sum_{s \in P5_a} OI_{s,j,t} - \frac{1}{n} \sum_{s \in P1_a} OI_{s,j,t}, \tag{12}$$

where $P1_a$ ($P5_a$) denotes the set of stocks in quintile portfolio 1 (5), sorted on anomaly signal a. Subsequently, we conduct time series regressions for each mispricing anomaly a and agent j to estimate the following model:

$$r^G_{a,t} = \alpha_{a,j} + \beta_{a,j} LSOI_{a,j,t} + \varepsilon_{a,j,t} \tag{13}$$

where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile and $LSOI_{a,j,t}$ is the long-short option order imbalance measure of trader type j, calculated over the same portfolios as $r^G_{a,t}$. Our specification entails running five distinct time series regressions, each corresponding to a particular agent j, for every mispricing anomaly a.

A large positive $LSOI_{a,j,t}$ for agent j indicates that the agent has built a positive exposure to stocks within the long portfolio (portfolio 5), relative to stocks within the short portfolio (portfolio 1). Consequently, we anticipate observing a significant and positive coefficient $\beta_{a,j}$ for agent j in cases where the agent trades counter to the direction of stock mispricings associated with mispricing anomaly a and the resulting demand pressure causes the option-implied synthetic stock prices to move away from the physical counterparts.

5.2 Findings

We start by discussing the results for the mispricing anomalies $Releven$ and $Ivol_{FF3}$, and consider the remaining mispricing anomalies afterwards. Table 7 shows regression coefficients for $LSOI$ of different trader types. For both mispricing anomalies, proprietary traders exhibit positive and statistically significant coefficients for the long-short option order imbalance measure. Specifically, we estimate coefficients of 0.50% (t-statistic of 3.56) for momentum and 0.39% (t-statistic of 2.06) for idiosyncratic volatility. These outcomes indicate that proprietary traders associated with financial institutions employ options to trade against the prevailing stock mispricing direction in both anomalies.

In the case of both momentum and idiosyncratic volatility, we observe negative coefficients for the long-short option order imbalance measure of the market maker, although these coefficients are not statistically significant. This suggests that the market maker, when engaging in trades with proprietary traders, tends to exhibit positive exposure to overvalued stocks in the short portfolio and negative exposure to undervalued stocks in the long portfolio. This aligns with the notion that the market maker charges a premium for the imperfectly hedgeable risk arising from such exposure, as outlined in Garleanu et al. (2009). These findings are consistent with our notion of informed investors being professionals in financial institutions with large research departments equipped with the capability to identify mispriced stocks.

Ge et al. (2016) find that option trading volume of proprietary traders does not forecast stock returns in the subsequent week. They posit that proprietary traders in financial institutions, equipped with access to actual leverage, may not need the synthetic leverage available in the options market. However, our analysis reveals a more nuanced picture. Where Ge et al. (2016) consider the full cross-section of optionable stocks, we focus here on particularly over- and undervalued stocks, as indicated by a high option trading volume and extreme instances of two mispricing anomaly signals. For $Releven$ and $Ivol_{FF3}$, we find that proprietary traders do engage in options trading to counteract stock mispricings. We contend that prop traders perceive stocks in the extreme portfolios as particularly attractive investment opportunities.

We find similar outcomes for further mispricing anomalies, though not consistently across all of them. Detailed results are provided in Table A3 in the appendix. Noteworthy examples include significant coefficients for the $LSOI$ of proprietary traders at the 5% significance level for anomalies such as $Rsix$ (momentum), $SALEP$ (value), PM (profitability), and $Rn1$ (intangibles). In total, among the 38 anomalies exhibiting significantly positive $OVIMS$, 11 anomalies demonstrate significantly positive coefficients for the $LSOI$ of proprietary traders at the 10% significance level (6 for professional customers, 3 for customers and 1 for broker-dealers).

5.3 Are the results driven by insider trading?

Bondarenko and Muravyev (2023) find that several option-based metrics lose their predictive power around 2009. The authors posit that this decline may be attributed to the contemporaneous arrest of Raj Rajaratnam and an unprecedented crackdown on insider trading. They suggest that these events may have deterred insiders from engaging in options trading, consequently diminishing the information content of option-based measures. To assess the potential impact of this phenomenon on our findings, we compute non-normalized OVIMS and unconditional conversion returns of anomalies starting from October 2009. Subsequently, we plot these results on their counterparts derived from the full sample period. The outcomes are depicted in Figure 6.

We find that the aforementioned events do not substantially alter our findings. First, anomalies exhibiting high non-normalized OVIMS throughout the full sample period largely maintain consistent estimates when examined over the short sample period between October 2009 and December 2018, as evidenced by their alignment around the 45-degree line. Similarly, anomalies demonstrating minimal non-normalized OVIMS across the full sample period tend to exhibit similarly modest values during the short sample period, albeit with slightly more variability around zero.

Second, we even find amplified conversion returns during the short sample period, particularly for anomalies characterized by large conversion returns throughout the full sample period. This suggests that informed traders increasingly counteract stock mispricings at the options market over this time period. At the same time, anomalies displaying negligible conversion returns over the full sample period demonstrate minimal conversion returns during the short sample period.

Importantly, our results do not contrast or invalidate the findings of Bondarenko and Muravyev (2023). While option-based metrics may no longer forecast returns on individual stocks post-2009, they could still align closely with anomaly signals. These signals are only very noisy signals of future returns. Additionally, Bondarenko and Muravyev (2023) confined their examination to S&P500 stocks, while our study encompasses all actively traded optionable common stocks.

6 When do they trade?

We investigate the timing of sophisticated traders' activities in acting against stock mispricings within the options market. We posit that their motivation is particularly strong in times when stock mispricings are pronounced, e.g. due to binding financial market frictions. In such periods, we expect large spreads between option-implied synthetic and actual stock prices. We therefore investigate whether these spreads are more substantial during periods characterized by elevated financial market frictions. Our analysis incorporates various indicators, quantifying the extent of short selling constraints, stock liquidity constraints, option liquidity constraints, intermediary capital constraints, and funding liquidity constraints.

6.1 Data

Short selling constraints Elevated stock borrowing fees represent a significant impediment when investors intend to counteract overvaluations. Prior studies suggest that investors frequently resort to the options market to implement synthetic shorting strategies (see e.g.

Figlewski and Webb (1993), Danielsen and Sorescu (2001), and Johnson and So (2012). Consequently, we anticipate an increase in option demand during periods of elevated short selling fees, leading to an increase in conversion returns. Notably, Muravyev et al. (2023b) recently derived a formula directly linking implied volatility spreads to stock borrowing fees, reinforcing the expectation of a positive relationship between conversion returns and short selling fees. Short selling fee data are sourced from the Markit Securities Finance dataset, specifically utilizing Markit's *INDICATIVEFEE*, representing the anticipated borrowing cost for a hedge fund on a given day. The dataset commences in July 2006, therefore for the subsequent analysis, we consider a sample period spanning from August 2006 to December 2018.

Stock and option liquidity constraints Apart from short selling constraints, various limitations impede informed investors from exploiting mispricings in both equity and options markets. When stocks are highly illiquid, the associated trading costs become prohibitive. In such scenarios, informed investors may find it advantageous to utilize options for trading against any mispricings. Consequently, we anticipate elevated conversion returns in periods of heightened stock illiquidity. Our metric for stock liquidity is derived from the bid-ask spread, as outlined in Corwin and Schultz (2012).

However, options trading may also incur costs due to illiquidity. We posit that during phases of elevated option illiquidity, there is a decrease in demand for options, leading to diminished conversion returns. Our measure of option liquidity is the quoted bid-ask spread of call options, calculated from the bid and ask prices in the OptionMetrics Ivy DB database's option price file. To align with the stock bid-ask spread, we compute monthly volume-weighted averages of daily call option bid-ask spreads for each stock.

Intermediary capital constraints A growing body of literature, exemplified by Adrian et al. (2014), He et al. (2017), and Haddad and Muir (2021), underscores the key role of financial intermediaries to act as marginal investors in numerous intermediated asset classes. This literature emphasizes the significance of the intermediary sector's health in comprehending the cross-sectional and time-series variations in stock and option returns. He et al. (2017) emphasize that the degree of intermediation is particularly pronounced in the options market. Our findings in Section 5 suggest that intermediaries, in their roles as prop traders, actively trade against mispricings in the options market. We anticipate that their demand will be pronounced during periods of elevated arbitrage capital and subdued during periods of diminished arbitrage capital. Consequently, we hypothesize a positive correlation between conversion returns and intermediary capital, utilizing the intermediary capital ratio proposed by He et al. (2017) in our analyses.

At the same time, intermediaries act as market makers in the stock and options market. Consequently, in times of low intermediary capital, market makers could be less willing to act as counterparty in the options market, leading to a more pronounced price impact of directional option trades. Following this line of argument, we expect a negative correlation between intermediary capital and conversion returns on mispricing anomalies.

Funding liquidity constraints The TED spread gauges the funding conditions within the financial intermediary sector, calculated as the disparity between the 3-month LIBOR rate and the 3-month T-bill rate. The underlying concept posits that a considerably elevated interbank lending rate in contrast to the risk-free interest rate for government bonds indicates heightened credit risk in the economy, reflecting a deterioration in funding conditions for intermediaries. As outlined above, such deterioration may lead to lower conversion returns as intermediaries, in their role as prop traders, may be less active in trading against mispricing anomalies in the options markets. In contrast, poorer financing conditions may discourage intermediaries from acting as market makers in the equity and options markets, leading to more pronounced price impact of end-user demand for options and, consequently, more pronounced conversion returns. Data on the TED spread is sourced from the Federal Reserve Bank of St. Louis.

6.2 Empirical approach

We estimate the following time series regression relating conversion returns of mispricing anomalies to market frictions:

$$\begin{aligned} r^G_{a,t} = \alpha_a + \beta_{a,sf} SF_{t-1} + \beta_{a,bas} BAS_{t-1} + \beta_{a,bao} BAO_{t-1} \\ + \beta_{a,icr} ICR_{t-1} + \beta_{a,ted} TED_{t-1} + r^G_{a,t-1} + \epsilon_{a,t} \end{aligned} \tag{14}$$

where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile in month t, SF_{t-1} is the cross-sectional average shorting fee at the end of month $t-1$, BAS_{t-1} is the cross-sectional average stock bid-ask spread at the end of month $t-1$, BAO_{t-1} is the cross-sectional average call option bid-ask spread at the end of month $t-1$, ICR_{t-1} is the intermediary capital ratio at the end of month $t-1$, TED_{t-1} is the TED spread at the end of month $t-1$ and $r^G_{a,t-1}$ is the one month lagged conversion long-short return of mispricing anomaly a. Importantly, the friction measures are realized at the end of the month prior to the initiation of the conversion positions, which takes place at the third Friday of the subsequent month. Thus, Equation (14) is really a predictive regression.

We standardize all independent variables to have a mean of zero and a standard deviation of one. Thus, the coefficients can be readily interpreted as the change to the monthly long-short conversion return corresponding to an anomaly when a friction measure increases by one standard deviation. An exception is the lagged conversion return, which we leave as it is, so that the coefficient can be interpreted as a first order auto-correlation coefficient, controlling for friction measures.

6.3 Empirical results

The regression coefficients corresponding to Equation (14) are presented in Table 8 for the two mispricing anomalies *Releven* and $Ivol\_FF3$. Notably, informed investors exhibit a propensity to trade options of mispriced stocks, particularly during periods characterized by elevated stock borrowing fees and diminished stock market liquidity. In the case of shorting fees, we observe positive and statistically significant coefficients of 0.15% (t-statistic of

6.94) and 0.10% (t-statistic of 4.07) per month for idiosyncratic volatility and momentum, respectively. Additionally, the stock bid-ask spread is found to be significant for idiosyncratic volatility, displaying a coefficient of 0.10% (t-statistic of 2.77). The substantial R^2 values of 31.15% and 23.80% for idiosyncratic volatility and momentum, respectively, underscore the considerable explanatory power of short selling and liquidity frictions in accounting for a substantial portion of the effect size of these anomalies in the stock market.

We provide numbers for all mispricing anomalies in Table A4 in the appendix. Our results reveal that besides short selling and stock liquidity constraints, funding liquidity constraints and intermediary capital constraints are also important ingredients in explaining conversion returns of some of the other mispricing anomalies. Two examples are Ole and Gla, both anomalies pertaining to the profitability category. For these two anomalies, we observe negative and statistically significant coefficients of -0.07% (t-statistic of -2.05) and -0.11% (t-statistic of -3.15) for the TED spread. Simultaneously, we find positive and statistically significant coefficients of 0.06% (t-statistic of 2.80) and 0.07% (t-statistic of 2.94) for the intermediary capital ratio. For both anomalies we find substantial R^2 values of 20.04% and 33.59%. This implies that informed investors trade options of mispriced stocks related to these two anomalies, particularly in periods of high funding liquidity and high arbitrage capital. These findings are in line with the notion of intermediaries acting as arbitrageurs and trading against anomalies especially in these periods.

We aggregate results for all 38 mispricing anomalies in Figure 7. For each friction that we consider in Equation (14), we plot the estimated coefficients for each anomaly in each category. Anomaly names printed in red indicate that the estimated coefficient is significant at the 5% level. Our findings suggest that short selling constraints play a predominant role as an explanatory variable. Positive and significant coefficients are observed for the majority of mispricing anomalies across all categories. Particularly noteworthy is the consistently positive and significantly estimated coefficients for all mispricing anomalies within the friction category. Stock liquidity constraints positively impact the conversion returns of mispricing anomalies, primarily within the friction and value categories. Funding liquidity constraints exhibit a negative influence on the conversion returns of mispricing anomalies, primarily within the profitability category. Similarly, intermediary capital constraints positively impact the conversion returns of mispricing anomalies only within the profitability category.

7 Conclusion

In recent years, the literature on empirical asset pricing has identified a multitude of patterns in the cross-section of expected stock returns that cannot be explained by common factor models—so-called anomalies. Nonetheless, within the academic literature, there remains an ongoing debate regarding the origins of these identified patterns—whether they stem from mispricing or, alternatively, arise as a result of consensual variation in discount rates, for example due to varying levels of systematic risk exposures across stocks. This study aims to systematically investigate and discern which among these patterns serve as particularly informative indicators of mispricing. This inquiry is of crucial importance, given that mispricing, if prevalent, introduces significant inefficiencies into the real economy.

Our approach for classifying anomalies rests on two fundamental yet natural assumptions. Firstly, we posit the existence of market participants endowed with the capability and resources to discern mispriced stocks. Secondly, we assert that these participants may find it optimal to engage in options trading on identified mispriced stocks. Consistent with this framework, we observe substantial and statistically significant long-short returns among stocks with high option trading activity across numerous cross-sectional asset pricing anomalies. Conversely, stocks with low option trading activity exhibit negligible long-short returns for these anomalies. Building upon these observations, we introduce an analytical measure termed the *Option Volume Implied Mispricing Score* ($OVIMS$), designed to quantify the informational content of anomalies regarding stock mispricing. Our findings reveal that anomalies associated with the *momentum*, *profitability*, and *friction* categories yield the highest $OVIMS$, indicating a strong association with stock mispricing. Conversely, anomalies within the *investment*, *value*, and *intangibles* categories exhibit less pronounced $OVIMS$.

To validate our empirical observation that sophisticated market participants engage in options trading concerning stocks influencing mispricing anomalies, we examine price wedges between option-implied synthetic stock positions and their corresponding underlying physical counterparts. This analysis allows us to discern the directional preferences of option traders. Our findings indicate that, particularly among stocks exhibiting elevated option trading volume and for anomalies characterized by a high $OVIMS$, i.e., mispricing anomalies, the option-implied synthetic stock prices for stocks within the short portfolio tend to be, on average, lower than their respective physical stock prices. Conversely, for stocks within the long portfolio, the option-implied synthetic stock prices are, on average, higher than their corresponding physical stock prices. In a broader context, we observe that, for the majority of high $OVIMS$ anomalies, long-short returns are more pronounced in the stock market than in the options market. In contrast, we find no significant distinctions in long-short returns between the stock and options markets for the majority of low $OVIMS$ anomalies, i.e., consensual anomalies. Our results provide compelling evidence supporting the notion that informed investors utilize options to strategically trade against stock mispricings, leading to markedly lower long-short returns for associated anomalies in the options market.

Our findings guide us to two central questions. First, who are the informed investors trading against mispricings at the options market? And second, does their trading activity exhibit systematic temporal variations? To answer the first question, we relate price differences between stock and option positions to agent-specific measures of option order imbalance. For certain mispricing anomalies, we find empirical evidence suggesting that the demand emanates from proprietary traders of financial institutions that moves the option-implied stock price away from the underlying stock price. These findings are consistent with the notion of informed investors being professionals in financial institutions with large research departments equipped with the capability to identify mispriced stocks.

To answer the second question, we associate anomalous stock-option price differences with market frictions. We find large stock-option price differences in periods of high short selling constraints for mispricing anomalies of all categories. Stock liquidity constraints mainly impact stock-option price differences of mispricing anomalies belonging to the friction and value category, while funding liquidity and intermediary constraints largely affect stock-option price differences of mispricing anomalies within the profitability category.

Our observations bear notable policy implications by suggesting that particularly trading costs, manifesting as short selling costs and stock liquidity, but also funding liquidity and frictions in the intermediary sector, impede the endeavor to enhance the efficiency of market mechanisms for capital allocation.

The fact that *momentum* and *profitability* are identified as mispricing anomaly signals through our measure is noteworthy. Not only do Frey (2023) and Bali et al. (2023) identify the same categories as associated to mispricing, using a completely different method, but these two categories are also identified by van Binsbergen et al. (2023) as so-called build-up anomalies. This means that, according to the authors, anomaly returns move prices even further away from fair values, rather than resolving mispricing. van Binsbergen et al. (2023, page 430) emphasize that "intermediaries that choose to trade in the same direction as a build-up anomaly may in fact be adversely affecting real economic allocations by further distorting price signals." Our results represent important stylized facts, crucial for gaining a better understanding of the mechanisms underlying these anomalies. This is an interesting and important task for future research.

Tables

Table 1: Anomaly returns and option trading volume

We match anomalies from Chen et al. (2023) and Bali et al. (2023) to those used in our study. Eleven anomalies (Ami, Dtv, $Releven$, RS, OA, $Rmom11$, $dNco$, Ivc, SR, $dNoa$, Tur, see Table A1 in the appendix for further information on the anomalies) are consistently classified as mispricing-based, while nine anomalies ($Beta\_Market$, Ivg, HR, dBe, $IG2$, RCA, Tan, $IG3$, $Coskw$) are consistently classified as risk/other-based by both papers. We calculate long-short quintile returns averaged across the anomalies in the respective categorizations. We do this unconditionally as well as conditionally on the option-to-stock volume (O/S, see Roll et al. (2010)) of the underlying. For the conditional sorts, we sort stocks in five portfolios by their O/S. In each portfolio, we then sort the stocks in five portfolios by their characteristic. We compute the equally weighted returns for each portfolio. In each O/S quintile, we create long-short portfolios that buy portfolio 5 and sell portfolio 1. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. 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 March 1996 to December 2018.

	Unconditional	O/S 1	O/S 5	Δ
Panel A: Mispricing anomalies				
H-L	0.27**	0.05	0.66***	0.61***
t	(2.48)	(0.36)	(4.67)	(5.67)
Panel B: Risk/other anomalies				
H-L	0.22**	0.23**	0.28**	0.05
t	(2.18)	(2.17)	(2.11)	(0.52)

Table 2: Simulated portfolio sorts conditional on OTV - Stock returns

We evaluate our theoretical framework in a simulation exercise. We consider 4000 stocks in the cross-section with an average risk-premium $\mu^{RP} = 0.01$ corresponding to a monthly window. We assume that the predictable part in returns is split evenly into the mispricing component and the risk premium component with $\sigma^M = \sigma^{RP} = 0.01$. Unpredictable noise in returns amounts to $\sigma^P = 0.1$ and we consider the cases of a perfect signal in Panel A ($\sigma^S = 0$) and a noisy signal in Panel B ($\sigma^S = 0.5$). Further, we consider informative but noisy characteristics with $\phi_j = 0.2$ and let ζ_j range between 0 and 1. 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 4,000 stocks into 5 × 5 portfolios. We first sort on OTV and then, within each OTV-quintile, on the simulated characteristic.

Panel A: $\sigma^S = 0$						
	$\zeta_j = 1$			$\zeta_j = 0$		
	low OTV		high OTV	low OTV		high OTV
low C_j	0.99	⋯	-0.65	0.37	⋯	0.38
⋮	⋮		⋮	⋮		⋮
high C_j	1.02	⋯	2.65	1.63	⋯	1.62
H-L	0.04	⋯	3.30	1.26	⋯	1.24
Panel B: $\sigma^S = 0.5$						
	$\zeta_j = 1$			$\zeta_j = 0$		
	low OTV		high OTV	low OTV		high OTV
low C_j	0.66	⋯	-0.20	0.38	⋯	0.37
⋮	⋮		⋮	⋮		⋮
high C_j	1.33	⋯	2.19	1.62	⋯	1.63
H-L	0.67	⋯	2.40	1.24	⋯	1.25

Table 3: Portfolio sorts conditional on O/S - Stock returns

In each month, we sort the stocks in five portfolios by their O/S. In each portfolio, we then sort the stocks in five portfolios by their momentum, idiosyncratic volatility, or annual change in book equity. We compute the equally weighted returns for each portfolio. In each O/S quintile, we create long-short portfolios that buy portfolio 5 and sell portfolio 1 to show the cross-sectional variation in returns according to each sorting criteria. We compute monthly stock returns from option maturity to option maturity. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. 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 March 1996 to December 2018.

			O/S			
	Low	2	3	4	High	H-L
Panel A: Releven						
Low	1.01	0.90	0.39	0.15	-0.32	-1.33
2	1.13	0.75	0.73	0.87	0.52	-0.61
3	1.04	0.92	0.85	0.85	0.50	-0.55
4	0.85	0.99	0.83	1.09	0.83	-0.02
High	1.01	0.85	1.15	0.90	0.80	-0.21
H-L	-0.01	-0.04	0.76	0.74	1.11^{***}	1.12^{***}
t	(-0.02)	(-0.12)	(1.30)	(1.35)	(2.79)	(3.70)
Panel B: $Ivol_{FF3}$						
Low	0.92	0.25	0.20	-0.07	-0.50	-1.42
2	0.97	1.00	0.60	0.68	0.17	-0.80
3	1.13	1.22	1.09	1.05	0.81	-0.32
4	0.96	0.92	1.04	1.09	1.01	0.05
High	1.04	0.97	0.96	1.07	0.81	-0.23
H-L	0.12	0.72^{*}	0.76	1.14^{**}	1.30^{***}	1.18^{***}
t	(0.29)	(1.66)	(1.38)	(2.51)	(3.12)	(4.53)
Panel C: dBE						
Low	0.82	1.19	0.74	0.45	-0.08	-0.90
2	1.13	1.12	0.96	0.99	0.78	-0.35
3	0.82	1.02	0.87	0.71	0.75	-0.07
4	1.17	0.84	0.92	1.08	0.85	-0.32
High	1.30	0.82	0.94	1.05	0.41	-0.88
H-L	0.47^{**}	-0.36	0.20	0.60^{*}	0.49^{*}	0.02
t	(2.52)	(-1.46)	(0.80)	(1.79)	(1.93)	(0.07)

Table 4: OVIMS across anomalies

We show $OVIMS$ for all anomalies that we consider in our analysis. We compute an anomaly's $OVIMS$ as the difference in long-short returns calculated on high O/S stocks and calculated on low O/S stocks. We normalize this difference by the maximum average long-short return across the O/S quintiles, that is a measure of the effect size. We report standard errors, t-values and bootstrapped confidence intervals of the mean. Specifically, we report 95% confidence intervals and use 20.000 iterations for the bootstrap. We adopt the anomaly categorization of Hou et al. (2020). All characteristics are signed so that a quintile portfolio sort results in a positive long-short return on our sample. We compute monthly stock returns from option maturity to option maturity. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from March 1996 to December 2018.

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
PPS	Frictions	1.23	0.25	4.90	[0.78,1.90]
Rsix	Momentum	1.09	0.24	4.46	[0.65,1.76]
Ami	Frictions	1.15	0.26	4.45	[0.71,1.86]
RNA	Profitability	1.23	0.31	4.00	[0.81,1.79]
Ole	Profitability	1.38	0.35	3.99	[0.88,1.93]
Dtv	Frictions	1.24	0.32	3.86	[0.75,1.89]
Ivol_Q	Frictions	0.91	0.24	3.83	[0.41,1.64]
Ivol_CAPM	Frictions	0.92	0.24	3.82	[0.45,1.73]
Ivol_FF3	Frictions	0.91	0.25	3.65	[0.43,1.72]
O	Profitability	1.07	0.31	3.46	[0.67,1.56]
Ope	Profitability	1.06	0.31	3.43	[0.62,1.74]
Gla	Profitability	1.03	0.32	3.22	[0.54,1.57]
Gpa	Profitability	0.86	0.27	3.22	[0.45,1.21]
Ndpq	Value	1.48	0.46	3.19	[0.70,1.94]
ME_June	Frictions	1.05	0.33	3.16	[0.49,1.79]
TVol	Frictions	0.89	0.29	3.02	[0.31,1.74]
Releven	Momentum	1.01	0.34	2.98	[0.39,1.74]
CashOP	Profitability	0.78	0.27	2.94	[0.34,1.07]
Ivol_AHT	Frictions	0.82	0.28	2.93	[0.32,1.75]
ATO	Profitability	0.98	0.34	2.90	[0.39,1.66]
Ebpq	Value	1.80	0.63	2.85	[0.48,1.94]
Rmom6	Momentum	0.99	0.36	2.77	[0.34,1.61]
PM	Profitability	1.06	0.39	2.76	[0.37,1.77]
Beta_Market	Frictions	0.99	0.37	2.65	[0.29,1.85]

Continued on next page

Table 4 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
Cto	Profitability	0.95	0.36	2.64	[0.32,1.61]
SALEP	Value	1.00	0.38	2.62	[0.32,1.75]
OL	Intangibles	1.06	0.42	2.53	[0.31,1.78]
Mdr	Frictions	0.76	0.30	2.52	[0.17,1.60]
dCol	Investment	1.14	0.46	2.46	[0.23,1.68]
Rn1	Intangibles	0.85	0.36	2.35	[0.15,1.58]
CashOPl	Profitability	0.71	0.31	2.31	[0.12,1.04]
Abr	Momentum	1.24	0.57	2.19	[0.13,1.79]
OBA	Intangibles	1.14	0.54	2.11	[0.10,1.81]
dFnl	Investment	0.81	0.38	2.11	[0.09,1.34]
Ola	Profitability	0.79	0.38	2.10	[0.04,1.40]
NPM	Value	0.91	0.45	2.01	[0.03,1.66]
Cei	Investment	0.69	0.35	2.00	[0.02,1.41]
RS	Momentum	0.84	0.43	1.94	[0.01,1.56]
EM	Value	0.93	0.49	1.92	[-0.05,1.66]
OA	Investment	1.89	0.98	1.92	[-0.03,1.94]
RDS	Intangibles	1.63	0.86	1.89	[-0.05,1.88]
OCFP	Value	0.90	0.50	1.78	[-0.09,1.69]
Rmom11	Momentum	0.65	0.37	1.78	[-0.09,1.21]
Opa	Profitability	0.64	0.36	1.76	[-0.09,1.03]
dLti	Investment	1.32	0.75	1.75	[-0.12,1.87]
SUE	Momentum	1.35	0.78	1.73	[-0.16,1.86]
Noa	Investment	0.75	0.44	1.72	[-0.10,1.37]
dNco	Investment	0.47	0.28	1.71	[-0.06,1.06]
I.A	Investment	0.61	0.37	1.65	[-0.12,1.05]
Ivc	Investment	0.97	0.60	1.62	[-0.20,1.60]
Etl	Intangibles	1.36	0.88	1.54	[-0.36,1.87]
CVDtv	Frictions	0.97	0.63	1.53	[-0.26,1.67]
EP	Value	0.68	0.45	1.50	[-0.29,1.60]
Eprd	Intangibles	0.46	0.31	1.47	[-0.19,0.87]
TS	Frictions	1.03	0.70	1.47	[-0.28,1.81]
Sm	Momentum	1.41	0.97	1.45	[-0.37,1.84]

Continued on next page

Table 4 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
BCA	Intangibles	0.78	0.56	1.40	[-0.24,1.51]
Wwi	Intangibles	0.99	0.74	1.33	[-0.47,1.76]
dGs	Intangibles	1.03	0.77	1.33	[-0.41,1.72]
TAM	Value	1.01	0.78	1.30	[-0.43,1.62]
Ivg	Investment	0.67	0.54	1.25	[-0.33,1.24]
dNca	Investment	0.40	0.33	1.20	[-0.25,1.07]
TR	Frictions	1.03	0.86	1.19	[-0.55,1.78]
SR	Value	0.96	0.89	1.08	[-0.57,1.62]
CV	Frictions	0.91	0.85	1.06	[-0.73,1.73]
CP	Value	0.67	0.64	1.05	[-0.70,1.54]
Tbi	Profitability	0.79	0.78	1.02	[-0.57,1.62]
ADM	Intangibles	0.69	0.70	1.00	[-0.56,1.51]
Iskew_Q	Frictions	1.42	1.41	1.00	[-0.88,1.86]
Ra1	Intangibles	0.53	0.56	0.95	[-0.57,1.28]
STR	Frictions	0.90	0.99	0.91	[-0.62,1.63]
BMa	Value	0.50	0.58	0.85	[-0.71,1.37]
HR	Intangibles	0.28	0.33	0.85	[-0.44,1.07]
Ra6_10	Intangibles	0.40	0.53	0.75	[-0.62,1.11]
Ala	Intangibles	0.62	0.85	0.73	[-0.82,1.36]
TPM	Value	0.45	0.63	0.71	[-0.89,1.33]
IG	Investment	0.42	0.59	0.70	[-0.75,1.34]
Lfe	Intangibles	0.54	0.76	0.70	[-0.73,1.31]
OCA	Intangibles	0.28	0.42	0.66	[-0.59,0.86]
dCoa	Investment	0.35	0.52	0.66	[-0.74,1.32]
Evr	Intangibles	1.22	1.86	0.65	[-1.07,1.72]
EBP	Value	0.52	0.92	0.57	[-0.85,1.39]
Kzi	Intangibles	0.52	0.92	0.57	[-0.98,1.53]
dNoa	Investment	0.17	0.31	0.56	[-0.45,0.86]
Ta	Investment	0.50	0.94	0.53	[-1.01,1.62]
dFin	Investment	0.22	0.43	0.52	[-0.76,1.09]
Ecs	Intangibles	0.40	0.89	0.45	[-1.15,1.49]
Iskew_CAPM	Frictions	0.35	0.76	0.45	[-1.04,1.39]

Continued on next page

Table 4 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
dPia	Investment	0.15	0.38	0.40	[-0.66,0.92]
Altman_Z	Profitability	0.41	1.06	0.39	[-1.02,1.49]
dSs	Intangibles	0.21	0.56	0.36	[-0.91,1.39]
Bl	Profitability	0.31	1.03	0.30	[-1.14,1.20]
RDM	Intangibles	0.13	0.66	0.20	[-0.82,1.18]
dNcl	Investment	0.12	0.61	0.20	[-1.09,1.24]
Pda	Investment	0.16	0.94	0.17	[-1.14,1.17]
dLno	Investment	0.06	0.33	0.17	[-0.65,0.73]
IOCA	Intangibles	0.07	0.46	0.16	[-0.89,0.84]
SG	Value	0.09	0.57	0.16	[-1.02,1.12]
Fra	Intangibles	0.07	0.54	0.13	[-0.97,1.03]
Log_Growth_BD	Investment	0.13	1.00	0.13	[-1.28,1.12]
TDM	Value	0.08	0.69	0.11	[-1.11,0.89]
Esm	Intangibles	0.22	3.22	0.07	[-1.53,1.53]
SVR	Frictions	0.05	0.80	0.06	[-1.20,0.89]
dBe	Investment	0.03	0.56	0.05	[-0.92,0.77]
gAD	Intangibles	-0.03	1.34	-0.02	[-1.49,1.48]
IG2	Investment	-0.04	0.58	-0.06	[-1.23,1.00]
dIi	Investment	-0.03	0.51	-0.06	[-1.03,0.83]
Rn6_10	Intangibles	-0.04	0.49	-0.07	[-0.94,0.87]
dWc	Investment	-0.06	0.82	-0.07	[-1.40,1.39]
Beta_Dimson	Frictions	-0.22	2.55	-0.08	[-1.43,1.33]
Alm	Intangibles	-0.05	0.62	-0.09	[-1.43,1.02]
Iadj_Rer	Intangibles	-0.07	0.74	-0.10	[-1.47,1.20]
RCA	Intangibles	-0.11	0.89	-0.12	[-1.18,1.01]
Epq	Value	-0.11	0.62	-0.17	[-1.44,0.81]
Sdd	Intangibles	-0.11	0.64	-0.17	[-1.32,1.13]
TES	Momentum	-0.65	3.74	-0.17	[-1.64,1.44]
beta.BD.lev	Frictions	-0.17	0.53	-0.32	[-1.37,0.79]
BMJ	Value	-0.23	0.71	-0.33	[-1.58,0.83]
Iskew_FF3	Frictions	-0.64	1.74	-0.36	[-1.66,1.18]
PS_Beta	Frictions	-0.58	1.17	-0.49	[-1.61,1.14]

Continued on next page

Table 4 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
Emq	Value	-0.36	0.72	-0.50	[-1.59,0.68]
dSti	Investment	-0.43	0.79	-0.54	[-1.63,0.96]
Frm	Intangibles	-0.42	0.76	-0.56	[-1.35,0.78]
Dac	Investment	-0.68	1.18	-0.57	[-1.74,1.02]
Rn2_5	Intangibles	-0.38	0.66	-0.57	[-1.62,0.64]
Tur	Frictions	-0.30	0.49	-0.61	[-1.46,0.52]
Tan	Intangibles	-0.96	1.44	-0.66	[-1.71,0.92]
Spq	Value	-0.35	0.52	-0.67	[-1.65,0.50]
Pta	Investment	-0.77	1.10	-0.70	[-1.76,0.92]
Ra2_5	Intangibles	-0.64	0.85	-0.75	[-1.61,0.78]
Etr	Intangibles	-0.66	0.82	-0.81	[-1.59,0.72]
Cpq	Value	-0.54	0.62	-0.86	[-1.65,0.50]
Dmq	Value	-0.73	0.83	-0.88	[-1.64,0.53]
dSa	Intangibles	-1.10	1.23	-0.90	[-1.75,1.00]
POA	Investment	-0.73	0.72	-1.01	[-1.63,0.55]
IG3	Investment	-0.78	0.69	-1.13	[-1.73,0.50]
Eper	Intangibles	-1.18	0.98	-1.20	[-1.76,0.57]
LTR	Value	-0.96	0.75	-1.28	[-1.81,0.37]
dSi	Intangibles	-1.98	1.42	-1.39	[-1.92,0.58]
Coskw	Frictions	-1.39	0.99	-1.40	[-1.86,0.46]
Ocpq	Value	-1.01	0.70	-1.45	[-1.83,0.26]
Amq	Value	-1.09	0.67	-1.62	[-1.75,0.18]
AvgCE	Investment	-1.73	0.94	-1.85	[-1.94,0.07]
NDP	Value	-1.31	0.62	-2.11	[-1.84,-0.07]

Table 5: Unconditional portfolio sorts - Stock, forward, and conversion returns
In each month, we sort the stocks in five portfolios by their momentum, idiosyncratic volatility, or annual change in book equity. We compute equally weighted stock returns, synthetic forward returns and conversion returns for each portfolio. We create long-short portfolios that buy portfolio 5 and sell portfolio 1 to show the cross-sectional variation in returns according to each sorting criteria. We compute conversion returns at the first trading day of an option pair. The stock returns are calculated accordingly over the one month to maturity of that same option pair. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. 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 March 1996 to December 2018.

	Releven			Ivol$_{FF3}$			dBE		
	r_S	r_F	r_G	r_S	r_F	r_G	r_S	r_F	r_G
Low	0.39	0.33	0.07	0.09	0.06	0.03	0.62	0.52	0.10
2	0.83	0.71	0.12	0.68	0.57	0.11	0.91	0.78	0.13
3	0.80	0.68	0.13	1.03	0.90	0.13	0.90	0.77	0.13
4	0.96	0.83	0.13	1.08	0.95	0.13	0.96	0.83	0.13
High	0.88	0.77	0.11	0.92	0.78	0.14	0.88	0.78	0.10
H-L	0.49	0.44	0.04***	0.83*	0.72	0.11***	0.26	0.26	0.00
t	(1.19)	(1.07)	(3.17)	(1.88)	(1.61)	(4.26)	(1.45)	(1.44)	(0.28)

Table 6: Portfolio sorts conditional on O/S - Conversion returns

In each month, we sort the stocks in five portfolios by their O/S. In each portfolio, we then sort the stocks in five portfolios by their momentum, idiosyncratic volatility, or annual change in book equity. We compute the equally weighted conversion returns for each portfolio. In each O/S quintile, we create long-short portfolios that buy portfolio 5 and sell portfolio 1 to show the cross-sectional variation in conversion returns according to each sorting criteria. We compute conversion returns at the first trading day of an option pair. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. 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 March 1996 to December 2018.

			O/S			
	Low	2	3	4	High	H-L
Panel A: Releven						
Low	0.12	0.11	0.11	0.07	-0.08	-0.20
2	0.14	0.13	0.12	0.13	0.08	-0.05
3	0.12	0.13	0.14	0.13	0.11	-0.02
4	0.11	0.13	0.14	0.15	0.11	-0.01
High	0.12	0.13	0.13	0.12	0.07	-0.06
H-L	0.00	0.03	0.02	0.05***	0.14***	0.14***
t	(0.23)	(1.53)	(1.02)	(3.02)	(5.22)	(4.25)
Panel B: $Ivol_{FF3}$						
Low	0.12	0.08	0.10	0.05	-0.14	-0.26
2	0.11	0.14	0.12	0.11	0.04	-0.06
3	0.13	0.13	0.14	0.14	0.11	-0.03
4	0.13	0.14	0.13	0.14	0.12	0.00
High	0.12	0.14	0.15	0.14	0.15	0.03
H-L	0.00	0.06***	0.05**	0.09***	0.29***	0.29***
t	(0.02)	(2.95)	(2.16)	(3.41)	(6.01)	(7.60)
Panel C: dBE						
Low	0.13	0.12	0.11	0.12	0.05	-0.09
2	0.13	0.13	0.14	0.14	0.09	-0.04
3	0.12	0.14	0.14	0.14	0.10	-0.02
4	0.12	0.13	0.14	0.13	0.12	0.00
High	0.12	0.13	0.12	0.12	0.04	-0.08
H-L	-0.01	0.01	0.01	0.00	-0.01	0.01
t	(-0.90)	(0.76)	(0.67)	(-0.36)	(-0.48)	(0.27)

Table 7: Regressions of conversion returns on LSOI

We regress a mispricing anomaly's long-short conversion return on its long-short option order imbalance. Specifically, we estimate the following model: $r^G_{a,t} = \alpha_{a,j} + \beta_{a,j} LSOI_{a,j,t} + \epsilon_{a,j,t}$, where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile in month t, and $LSOI_{a,j,t}$ is the long-short option order imbalance measure of trader type j, calculated over the same portfolios as $r^G_{a,t}$, in month t. For each mispricing anomaly, we estimate five time series regressions, one for each trader type. Cust, ProC, BD, Prop and MM are the regressions where we use the LSOI of trader type customer, professional customer, broker-dealer, proprietary trader and market maker. We compute conversion returns at the first trading day of an option pair. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. T-statistics are calculated using Newey and West (1987) standard errors. $*$, $**$, and $***$ indicate significance at the 10%, 5% and 1% level. Estimates and R^2 are displayed in percent. The sample covers the period from May 2005 to December 2018. Note that the ISE introduced professional customers only in October 2009. Therefore, the time series pertaining to professional customers starts from October 2009.

	Cust	ProC	BD	Prop	MM
Panel A: Releven					
const	0.20***	0.22***	0.19***	0.19***	0.20***
	(5.85)	(6.72)	(6.90)	(6.97)	(5.24)
β	-0.03	-0.15	0.40	0.50***	-0.06
	(-0.63)	(-0.46)	(1.39)	(3.56)	(-1.35)
R^2_{adj}	-0.43	-0.73	0.48	5.97	-0.07
Panel B: $Ivol_{FF3}$					
const	0.42***	0.47***	0.42***	0.42***	0.43***
	(10.74)	(15.37)	(9.54)	(11.91)	(11.50)
β	-0.07	-0.26	0.33	0.39**	-0.03
	(-0.73)	(-0.68)	(0.82)	(2.06)	(-0.30)
R^2_{adj}	-0.22	-0.49	0.18	2.46	-0.53

Table 8: Regressions of conversion returns on frictions

We regress a mispricing anomaly's long-short conversion return on market frictions. Specifically, we estimate the following model: $r^G_{a,t} = \alpha_a + \beta_{a,sf}SF_{t-1} + \beta_{a,bas}BAS_{t-1} + \beta_{a,bao}BAO_{t-1} + \beta_{a,hkm}ICR_{t-1} + \beta_{a,ted}TED_{t-1} + r^G_{a,t-1} + \epsilon_{a,t}$, where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile in month t, SF_{t-1} is the cross-sectional average shorting fee at the end of month $t-1$, BAS_{t-1} is the cross-sectional average stock bid-ask spread at the end of month $t-1$, BAO_{t-1} is the volume-weighted cross-sectional average call option bid-ask spread at the end of month $t-1$, ICR_{t-1} is the intermediary capital ratio at the end of month $t-1$, TED_{t-1} is the TED spread at the end of month $t-1$ and $r^G_{a,t-1}$ is the one month lagged conversion long-short return of mispricing anomaly a. The independent variables are normalized to have zero mean and unit standard deviation. We compute conversion returns at the first trading day of an option pair. The sample we consider consists only of optionable stocks that are in the top O/S quintile. We exclude financial firms and firms with negative book equity. T-statistics are calculated using Newey and West (1987) standard errors. $*$, $**$, and $***$ indicate significance at the 10%, 5% and 1% level. Estimates and R^2 are displayed in percent. Note that the data on the shorting fee starts in 2006, so that the sample period we consider is from August 2006 to December 2018.

	const.	SF	BAS	BAO	ICR	TED	Lag	R^2_{adj}
Releven	0.18***	0.10***	0.02	0.04	-0.03	-0.01	16.39	23.80
	(7.54)	(4.07)	(0.77)	(1.56)	(-0.86)	(-0.41)	(1.63)	
Ivol_FF3	0.44***	0.15***	0.10***	-0.00	0.00	-0.04	3.12	31.15
	(9.42)	(6.94)	(2.77)	(-0.12)	(0.10)	(-1.02)	(0.37)	

Figures

Figure 1: Simulated OVIMS
We show $OVIMS_j$ as a function of ζ_j for the situations of a perfect ($\sigma^S = 0$) and a noisy ($\sigma^S = 0.5$) signal. ζ_j indicates the degree to which a characteristic j is informative about the mispricing component relative to the consensual component in discount rates. For example, a characteristic with $\zeta_j = 1$ is only informative about mispricing but does not capture consensual variation in discount rates.

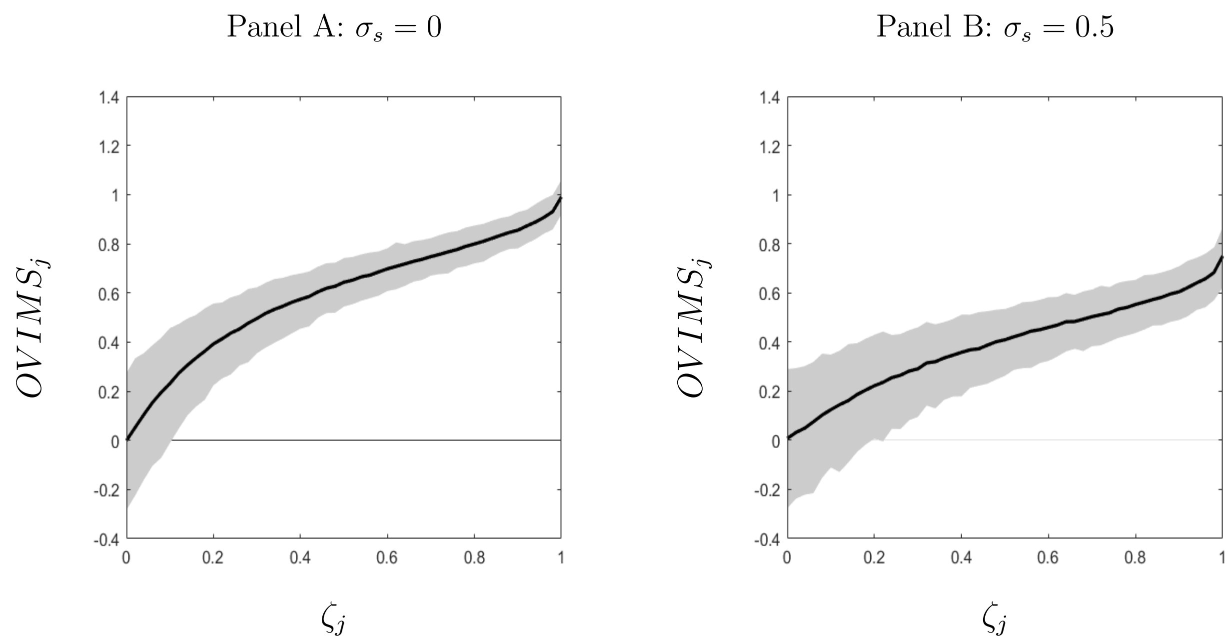


Figure 2: OVIMS and alphas

We plot an anomaly's unconditional, full sample alpha against its $OVIMS$. We consider alphas in relation to the $CAPM$, $FF3$-factor model, $FF5$-factor model and the Q-factor model. All characteristics are signed so that a quintile portfolio sort results in a positive long-short return on our sample. We compute monthly stock returns from option maturity to option maturity. To ensure consistency between the timing of our anomaly portfolio returns and factor returns, we also compute factor returns from option maturity to option maturity. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from March 1996 to December 2018.

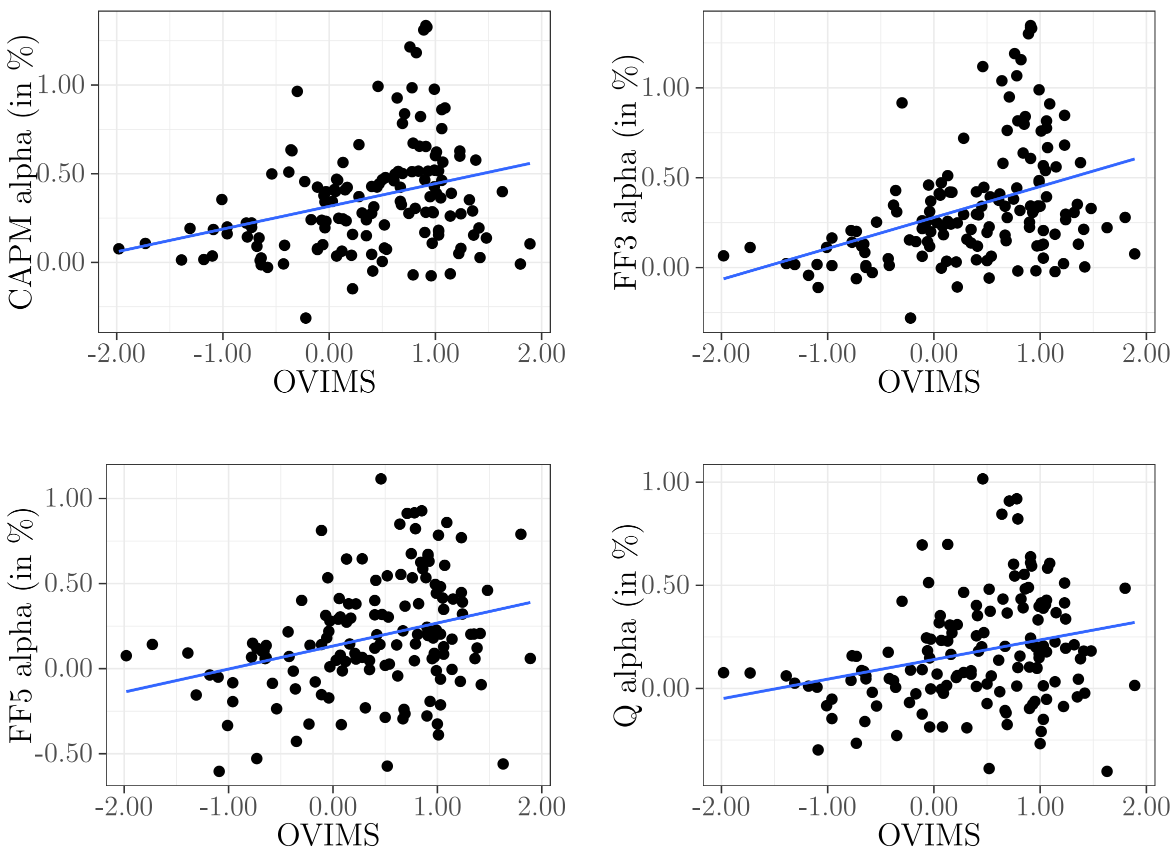


Figure 3: OVIMS in relation to other mispricing measures
We compare $OVIMS$ to the mispricing measures of Bali et al. (2023) (BBW), Chen et al. (2023) (CLZ), van Binsbergen et al. (2023) ($BBOT$) and Frey (2023) ($Frey$). We manually match the respective anomalies and measures to the corresponding anomalies used in our analysis. For the measures of BBW, CLZ and $Frey$, we create a dummy variable indicating whether the authors classify the anomaly as mispricing-based. For the measure of $BBOT$, we report the original price wedges, as the categorization differs from other authors. We plot the mispricing dummies of the matched anomalies on $OVIMS$. We fit a logit model which indicates the probability of an anomaly to be classified as mispricing-based by the respective author. Additionally, for $BBOT$, we fit a linear model as the dependent variable is not binary.

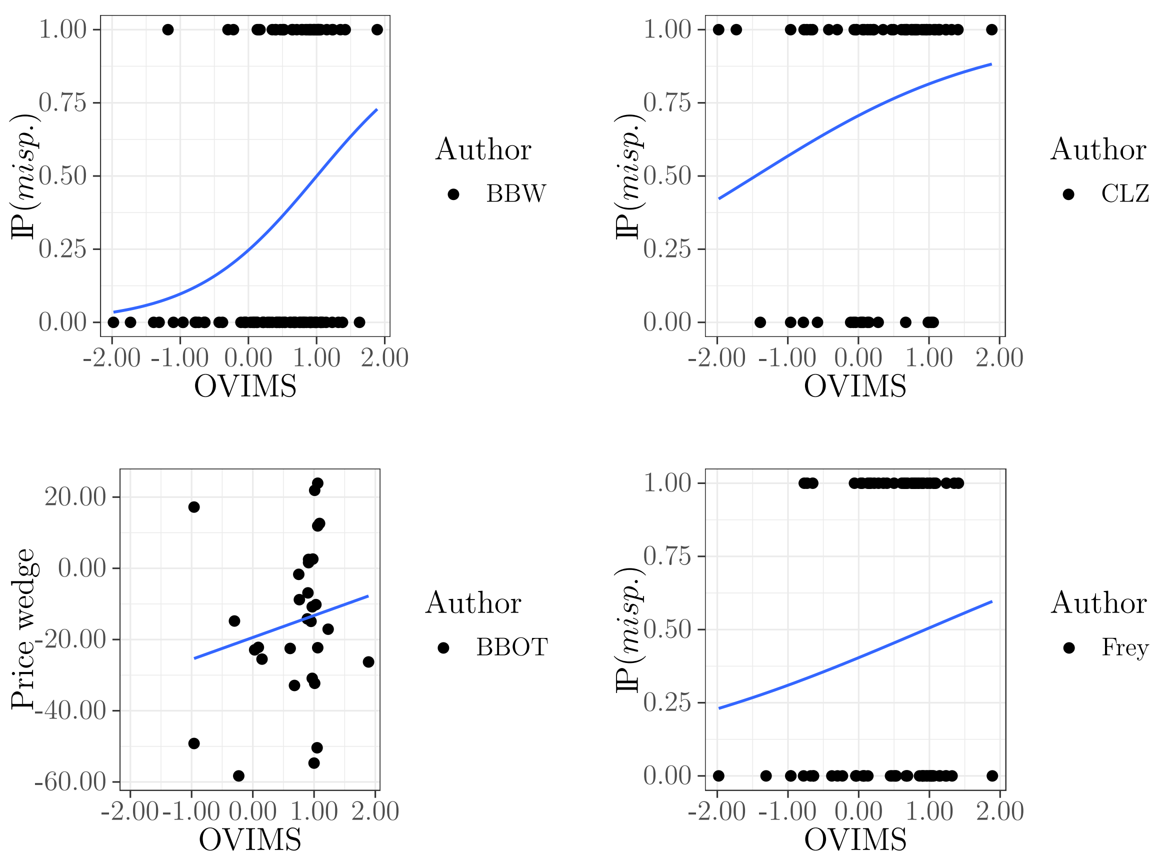


Figure 4: OVIMS and unconditional conversion returns

We plot unconditional conversion long-short returns of anomalies against their non-normalized $OVIMS$. We compute an anomaly's $OVIMS$ as the difference in long-short returns among stocks with high O/S and stocks with low O/S. We normalize this difference by the maximum long-short return across the O/S quintiles, that is a measure of the effect size. We compute conversion returns at the first trading day of an option pair. The stock returns are calculated accordingly over the one month to maturity of that same option pair. We compute equally weighted portfolio returns for each anomaly. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from March 1996 to December 2018.

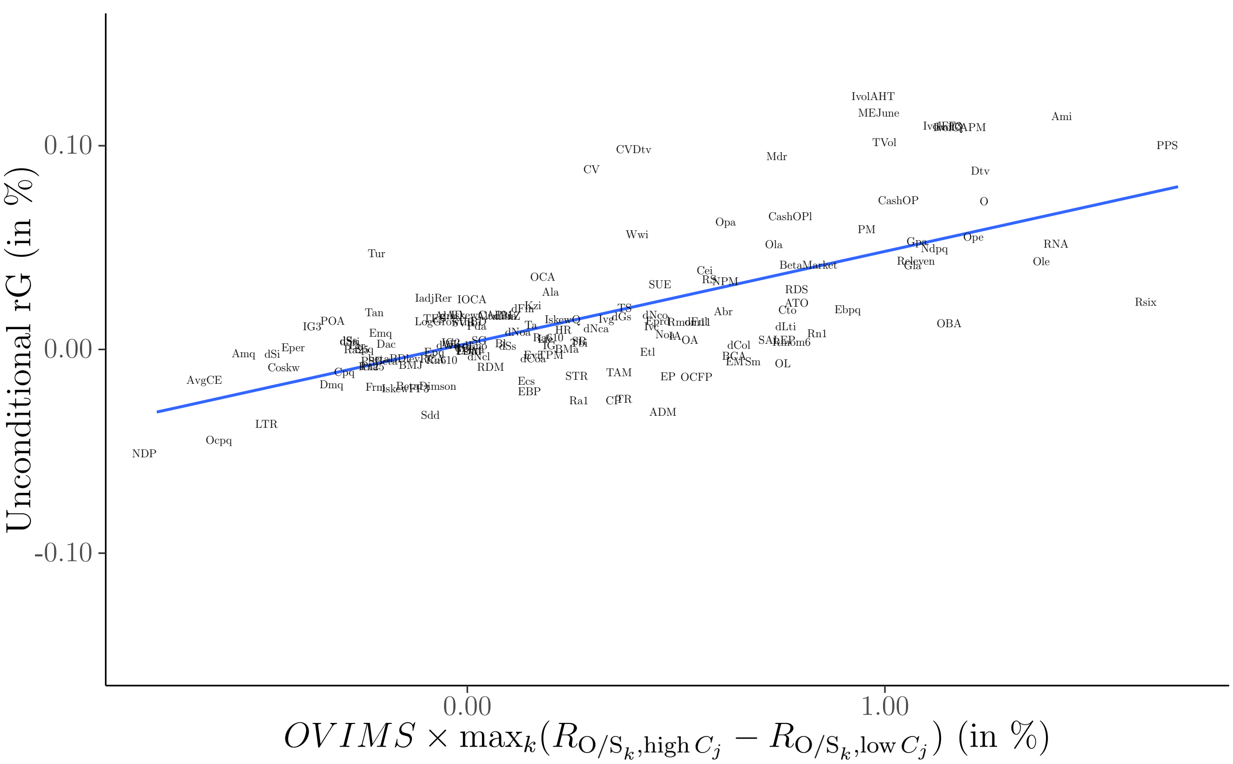


Figure 5: OVIMS and conditional conversion returns
We assign anomalies into five buckets based on their non-normalized $OVIMS$. In each of these five buckets we calculate the mean non-normalized $OVIMS$ and the mean conditional conversion returns. We plot average conditional conversion long-short returns of anomalies against their average non-normalized $OVIMS$. We compute an anomaly's $OVIMS$ as the difference in long-short returns among stocks with high O/S and stocks with low O/S. We normalize this difference by the maximum long-short return across the O/S quintiles, that is a measure of the effect size. $OS1$ shows the conversion long-short returns among low O/S stocks. $OS5$ shows the conversion long-short returns among high O/S stocks. We compute conversion returns at the first trading day of an option pair. The stock returns are calculated accordingly over the one month to maturity of that same option pair. We compute equally weighted portfolio returns for each anomaly. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from March 1996 to December 2018.

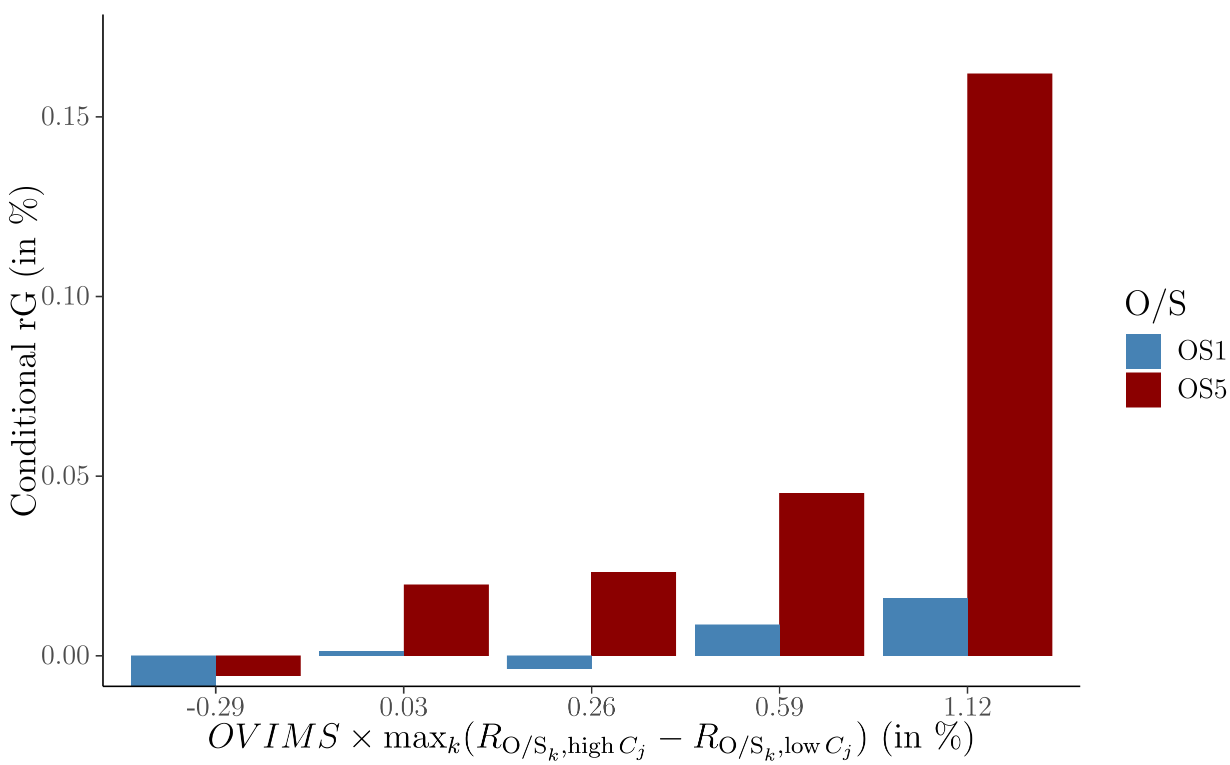


Figure 6: Long and short sample comparison

To assess whether our results are influenced by the unprecedented campaign against insider trading launched in 2009 (see Bondarenko and Muravyev (2023)), we plot non-normalized $OVIMS$ and unconditional conversion returns of anomalies calculated over the period from October 2009 to December 2018 on their full sample counterparts. The full sample covers the period from March 1996 to December 2018. The dashed line indicates the 45° line. We compute conversion returns at the first trading day of an option pair. The stock returns are calculated accordingly over the one month to maturity of that same option pair. We compute equally weighted portfolio returns for each anomaly. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity.

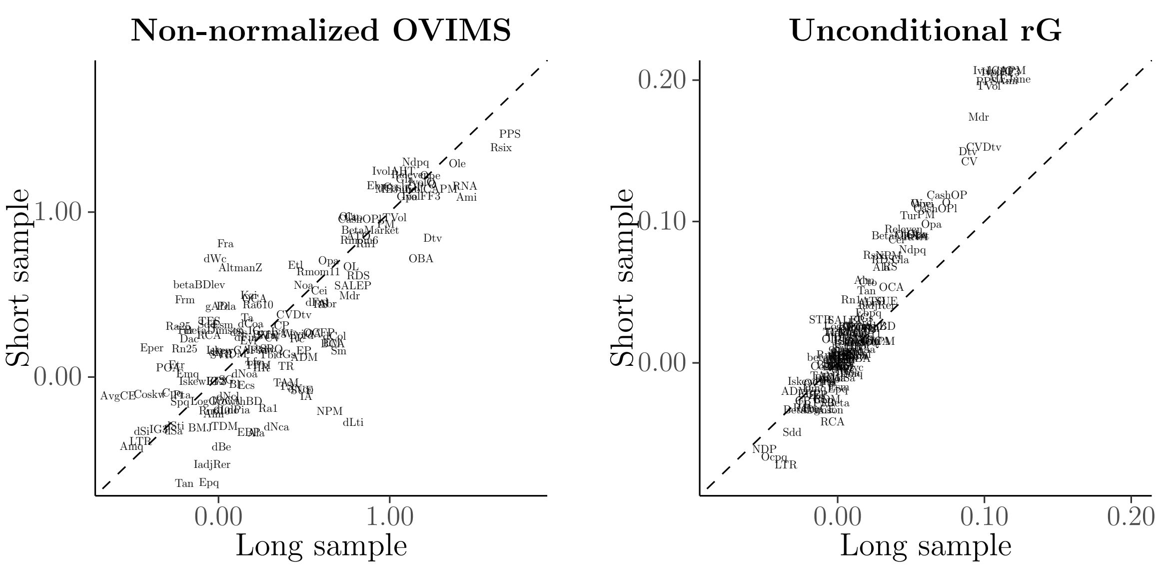
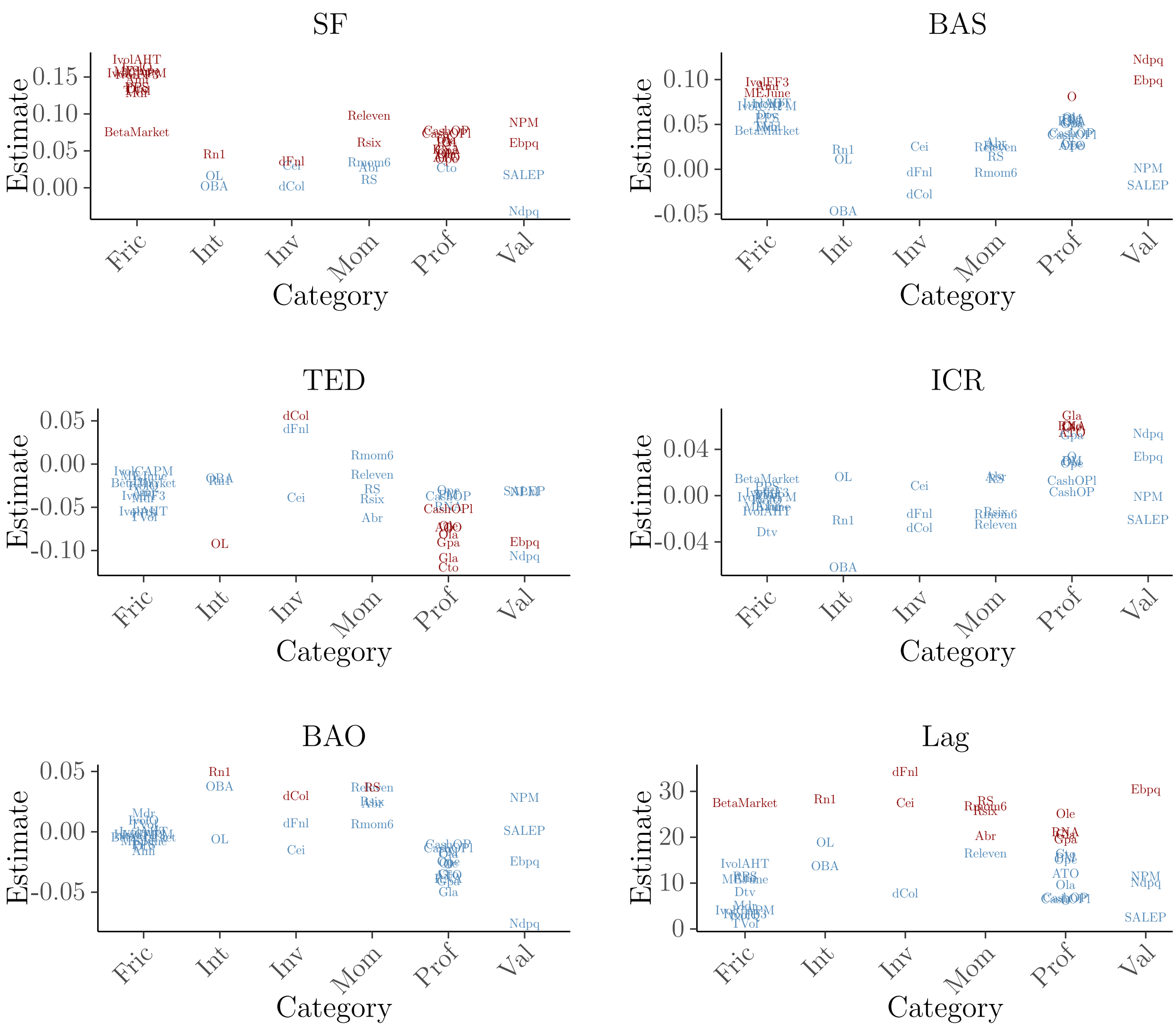


Figure 7: Conversion returns and frictions

For every mispricing anomaly, i.e. an anomaly with a significantly positive OVIMS, we estimate the following model: $r^G_{a,t} = \alpha_a + \beta_{a,sf} SF_{t-1} + \beta_{a,bas} BAS_{t-1} + \beta_{a,bao} BAO_{t-1} + \beta_{a,icr} ICR_{t-1} + \beta_{a,ted} TED_{t-1} + r^G_{a,t-1} + \epsilon_{a,t}$, where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile in month t, SF_{t-1} is the cross-sectional average shorting fee at the end of month $t-1$, BAS_{t-1} is the cross-sectional average stock bid-ask spread at the end of month $t-1$, BAO_{t-1} is the volume-weighted cross-sectional average call option bid-ask spread at the end of month $t-1$, ICR_{t-1} is the intermediary capital ratio at the end of month $t-1$, TED_{t-1} is the TED spread at the end of month $t-1$ and $r^G_{a,t-1}$ is the one month lagged conversion long-short return of mispricing anomaly a. We compute equally weighted conversion returns for each anomaly. We then plot the estimated coefficients for each friction separately for all categories of anomalies. A red anomaly name indicates that the estimated coefficient is significant at the 5% level for this anomaly. T-statistic are calculated using Newey and West (1987) standard errors. Estimates are displayed in percent. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from August 2006 to December 2018.



References

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. Journal of Finance 69, 2557–2596.

Ali, A., Hwang, L.S., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355–373.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223–249.

Bali, T.G., Beckmeyer, H., Wiedemann, T., 2023. Expected mispricing. Working paper .

Beckmeyer, H., Filippou, I., Zhou, G., 2023. A new option momentum: Compensation for risk. Working Paper.

van Binsbergen, J.H., Boons, M., Opp, C.C., Tamoni, A., 2023. Dynamic asset (mis) pricing: Build-up versus resolution anomalies. Journal of Financial Economics 147, 406–431.

Binsbergen, J.H.V., Opp, C.C., 2019. Real anomalies. Journal of Finance 74, 1659–1706.

Böll, J., Thimme, J., Uhrig-Homburg, M., 2023. Anomalies and optionability. Working Paper.

Bondarenko, O., Muravyev, D., 2023. What information do informed traders use? Working Paper.

Chen, A.Y., Lopez-Lira, A., Zimmermann, T., 2023. Peer-reviewed theory does not help predict the cross-section of stock returns. Working paper .

Chen, A.Y., Zimmermann, T., 2021. Open source cross-sectional asset pricing. Critical Finance Review, Forthcoming .

Christoffersen, P., Goyenko, R., Jacobs, K., Karoui, M., 2018. Illiquidity premia in the equity options market. Review of Financial Studies 31, 811–851.

Corwin, S.A., Schultz, P., 2012. A simple way to estimate bid-ask spreads from daily high and low prices. Journal of Finance 67, 719–760.

Daniel, K.D., Hirshleifer, D., Subrahmanyam, A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing. Journal of Finance 56, 921–965.

Danielsen, B.R., Sorescu, S.M., 2001. Why do option introductions depress stock prices? a study of diminishing short sale constraints. Journal of Financial and Quantitative Analysis 36, 451–484.

Donangelo, A., 2021. Untangling the value premium with labor shares. Review of Financial Studies 34, 451–508.

Drechsler, I., Drechsler, Q.F., 2021. The shorting premium and asset pricing anomalies. Working Paper.

Duarte, J., Jones, C.S., Mo, H., Khorram, M., 2023. Too good to be true: Look-ahead bias in empirical option research. Working Paper.

Easley, D., O'hara, M., Srinivas, P.S., 1998. Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance 53, 431–465.

Engle, R., Neri, B., 2010. The impact of hedging costs on the bid and ask spread in the options market. Working Paper, New York University.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–53.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Figlewski, S., Webb, G.P., 1993. Options, short sales, and market completeness. Journal of Finance 48, 761–777.

Frey, J., 2023. Which stock return predictors reflect mispricing? Working Paper.

Garleanu, N., Pedersen, L.H., Poteshman, A.M., 2009. Demand-based option pricing. Review of Financial Studies 22, 4259–4299.

Ge, L., Lin, T.C., Pearson, N.D., 2016. Why does the option to stock volume ratio predict stock returns? Journal of Financial Economics 120, 601–622.

Goyal, A., Saretto, A., 2009. Cross-section of option returns and volatility. Journal of Financial Economics 94, 310–326.

Grauer, C., Schuster, P., Uhrig-Homburg, M., 2023. Option trade classification. Working Paper.

Haddad, V., Muir, T., 2021. Do intermediaries matter for aggregate asset prices? Journal of Finance 76, 2719–2761.

He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: new evidence from many asset classes. Journal of Financial Economics 126, 1–35.

Hiraki, K., Skiadopoulos, G.S., 2021. The contribution of frictions to expected returns: An options-based estimation approach. Working Paper.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

Hou, K., Xue, C., Zhang, L., 2020. Replicating anomalies. The Review of Financial Studies 33, 2019–2133.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jensen, T.I., Kelly, B., Pedersen, L.H., 2023. Is there a replication crisis in finance? Journal of Finance 78, 2465–2518.

Johnson, T.L., So, E.C., 2012. The option to stock volume ratio and future returns. Journal of Financial Economics 106, 262–286.

Kogan, L., Papanikolaou, D., 2014. Growth opportunities, technology shocks, and asset prices. Journal of Finance 69, 675–718.

Muravyev, D., Pearson, N.D., Pollet, J.M., 2023a. Anomalies and their short-sale costs. Working Paper.

Muravyev, D., Pearson, N.D., Pollet, J.M., 2023b. Why does options market information predict stock returns? Working paper.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Ofek, E., Richardson, M., Whitelaw, R.F., 2004. Limited arbitrage and short sales restrictions: Evidence from the options markets. Journal of Financial Economics 74, 305–342.

Pan, J., Poteshman, A.M., 2006. The information in option volume for future stock prices. Review of Financial Studies 19, 871–908.

Richardson, S.A., Sloan, R.G., Soliman, M.T., Tuna, I., 2005. Accrual reliability, earnings persistence and stock prices. Journal of Accounting and Economics 39, 437–485.

Roll, R., Schwartz, E., Subrahmanyam, A., 2010. O/s: The relative trading activity in options and stock. Journal of Financial Economics 96, 1–17.

Appendix to
Following the Footprints: Towards a Taxonomy of the Factor Zoo

Julian Böll[‡] Fanchen Meng[§] Julian Thimme[¶] Marliese Uhrig-Homburg[‖]

This version: April 23, 2024

Abstract

This appendix complements the main text of "Following the Footprints: Towards a Taxonomy of the Factor Zoo" by providing additional figures and tables. Figure A1 shows our replication performance of anomalies. Table A1 gives a comprehensive overview over the anomalies used in our analyses. Table A2 provides data on $OVIMS$ and conversion returns of anomalies. Table A3 provides regression data on conversion returns and $LSOI$. Table A4 provides regression data on conversion returns and financial market frictions. Table A5 shows $OVIMS$ across anomalies when only considering out-of-the-money option trading volume.

[‡]Karlsruhe Institute of Technology, Germany, Email: julian.boell@kit.edu.
[§]Karlsruhe Institute of Technology, Germany, Email: fanchen.meng@kit.edu.
[¶]Karlsruhe Institute of Technology, Germany and University of Tübingen, Germany, Email: thimme@kit.edu.
[‖]Karlsruhe Institute of Technology, Germany and Georg-August-University Göttingen, Germany, Email: uhrig@kit.edu.

Appendix A

For the replication of anomaly portfolios, we use stock data from the Center for Research in Security Prices (CRSP), accounting data from the Compustat annual and quarterly files and analysts' earnings forecasts from the Institutional Brokers' Estimate System (I/B/E/S). We mainly rely on the appendix of Hou et al. (2020) and replicate a total of 144 anomalies. All our anomalies are based on one-month holding periods, in contrast to Hou et al. (2020), who consider 6-months or 12-months holding period versions for many anomaly signals. We also adopt their categorization of anomalies into six groups, namely momentum (9 anomalies), value (25 anomalies), trading frictions (25 anomalies), investment (31 anomalies), profitability (16 anomalies), and intangibles (38 anomalies). Table A1 provides an overview of the anomalies that we consider in our analysis.

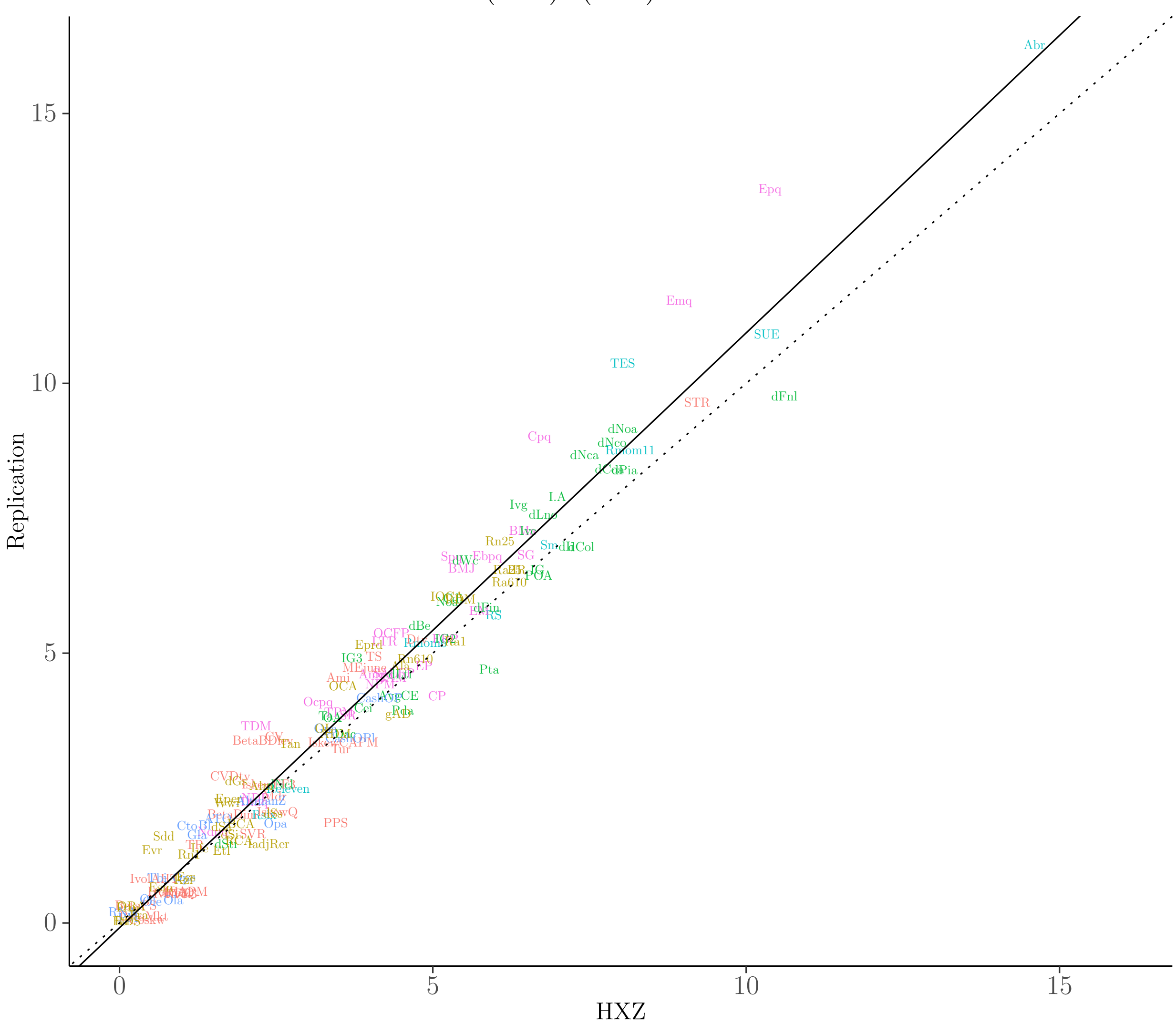
As a sanity check, we compare the t-statistics of our replication with those reported in the paper by Hou et al. (2020). For this purpose, we consider equally weighted returns of long-short decile portfolios. The universe of stocks is the entire cross-section of U.S. common stocks. We also use the entire cross-section to set breakpoints for the decile portfolios, i.e., we go long 10% of the stocks and short 10% of the stocks at each point in time. The time period considered corresponds to the choice of Hou et al. (2020), i.e., the sample generally starts in January 1967 and extends to December 2016. Due to data limitations, some anomaly signals are only available later than 1967. In those cases, we again use the same time frame as Hou et al. (2020).

Figure A1 shows that we successfully replicate the values reported in Hou et al. (2020). We regress our replicated t-statistics on those reported in their paper and find an insignificant intercept, a slope coefficient close to 1, and an R^2 of 96%.

Figures

Figure A1: 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).

$$\underset{(0.09)}{\text{Replication} = -0.09} + \underset{(0.02)}{1.10} * \text{HXZ} + \varepsilon,\ R^2 = 96\%$$



Tables

Table A1: Overview over anomalies
This table describes the anomalies that we use in our analyses.

Anomaly ID	Explanation	Original Paper
	Momentum	
SUE	Earnings surprise	Foster et al. (1984)
Abr	CAR around earnings announcements	Chan et al. (1996)
Rsix	Six months momentum	Jegadeesh and Titman (1993)
Releven	Eleven months momentum	Jegadeesh and Titman (1993)
TES	Tax expense surprise	Thomas and Zhang (2011)
Sm	Segment momentum	Cohen and Lou (2012)
Rmom11	Residual momentum over eleven months	Blitz et al. (2011)
Rmom6	Residual momentum over six months	Blitz et al. (2011)
RS	Revenue surprise	Jegadeesh and Livnat (2006)
	Value	
BMa	Book-to-market	Barr Rosenberg and Lanstein (1998)
BMJ	Book-to-June-Market	Clifford and Frazzini (2013)
TDM	Debt-to-Market	Bhandari (1988)
TAM	Assets-to-Market	Fama and French (1992)
EP	Earnings-to-price	Basu (1983)
CP	Cash flow-to-price	Lakonishok et al. (1994)
TPM	Payout yield	Boudoukh et al. (2007)
NPM	Net payout yield	Boudoukh et al. (2007)
NDP	Net debt-to-price	Penman et al. (2007)
EBP	Enterprise book-to-price	Penman et al. (2007)
OCFP	Operating cash flow-to-price	Desai et al. (2004)
SALEP	Sales-to-price	Barbee Jr et al. (1996)
EM	Enterprise multiple	Loughran and Wellman (2011)
SG	Sales growth	Lakonishok et al. (1994)
SR	5-year sales growth rank	Lakonishok et al. (1994)
Dmq	Debt-to-Market quarterly	Bhandari (1988)
AMq	Assets-to-Market quarterly	Fama and French (1992)

Continued on next page

Table A1 – continued from previous page

Anomaly ID	Explanation	Original Paper
LTR	Long-term reversal	De Bondt and Thaler (1985)
Epq	Earnings-to-price quarterly	Basu (1983)
Cpq	Cash flow-to-price quarterly	Lakonishok et al. (1994)
Emq	Enterprise multiple quarterly	Loughran and Wellman (2011)
Spq	Sales-to-price quarterly	Barbee Jr et al. (1996)
Ocpq	Operating cash flow-to-price quarterly	Desai et al. (2004)
Ebpq	Enterprise book-to-price quarterly	Penman et al. (2007)
Ndpq	Net debt-to-price quarterly	Penman et al. (2007)
	Trading frictions	
ME_June	Market equity	Banz (1981)
Ami	Absolute return-to-volume	Amihud (2002)
PS_Beta	Pastor/Stambaugh liquidity beta	Pástor and Stambaugh (2003)
Ivol_FF3	Ivol relative to FF3 model	Ang et al. (2006)
Ivol_AHT	Ivol relative to market	Ali et al. (2003)
Ivol_CAPM	Ivol relative to market	Ang et al. (2006)
beta_lev	Financial intermediary leverage beta	Adrian et al. (2014)
STR	Short-term reversal	Jegadeesh (1990)
TR	Tail risk	Kelly and Jiang (2014)
Coskw	Coskewness	Harvey and Siddique (2000)
Mdr	Maximum daily return	Bali et al. (2011)
PPS	Price per share	Miller and Scholes (1982)
Tur	Share turnover	Datar et al. (1998)
CV	Coef. of variation for share turnover	Chordia et al. (2001)
Dtv	Dollar trading volume	Brennan et al. (1998)
TVol	Total volatility	Ang et al. (2006)
SVR	Systematic volatility	Ang et al. (2006)
Beta	Fama/MacBeth Beta	Fama and MacBeth (1973)
TS	Total skewness	Bali et al. (2016)
Iskew_CAPM	Idiosyncratic skewness relative to market	Hou et al. (2020)
Iskew_FF3	Idiosyncratic skewness relative to FF3 model	Hou et al. (2020)
CVDtv	Coef. of variation for dollar trading volume	Chordia et al. (2001)

Continued on next page

Table A1 – continued from previous page

Anomaly ID	Explanation	Original Paper
Iskew_Q	Idiosyncratic skewness relative to Q-factor model	Hou et al. (2020)
Ivol_Q	Ivol relative to Q-factor model	Hou et al. (2020)
Dimson	Dimson Beta	Dimson (1979)
	Investment	
I_A	Investment-to-assets	Cooper et al. (2008)
Aci	Abnormal corporate investment	Titman et al. (2004)
dPia	Change in PPE and inventory to book assets	Lyandres et al. (2008)
Noa	Net operating assets	Hirshleifer et al. (2004)
dNoa	Change in net operating assets	Hirshleifer et al. (2004)
dLno	Change in long-term net operating assets	Fairfield et al. (2003)
IG	Investment growth	Xing (2008)
IG2	2-year investment growth	Anderson and Garcia-Feijóo (2006)
IG3	3-year investment growth	Anderson and Garcia-Feijóo (2006)
dIi	Change in investments relative to industry	Abarbanell and Bushee (1998)
Cei	Composite equity issuance	Daniel and Titman (2006)
Cdi	Composite debt issuance	Lyandres et al. (2008)
Ivg	Inventory growth	Belo and Lin (2012)
Ivc	Inventory changes	Thomas and Zhang (2002)
OA	Operating accruals	Sloan (1996)
Ta	Total accruals	Richardson et al. (2005)
dWc	Change in net noncash working capital	Richardson et al. (2005)
dCoa	Change in current operating assets	Richardson et al. (2005)
dCol	Change in current operating liabilities	Richardson et al. (2005)
dNco	Change in net noncurrent operating assets	Richardson et al. (2005)
dNca	Change in noncurrent operating assets	Richardson et al. (2005)
dNcl	Change in noncurrent operating liabilities	Richardson et al. (2005)
dFin	Change in net financial assets	Richardson et al. (2005)
dSti	Change in short-term investments	Richardson et al. (2005)
dLti	Change in long-term investments	Richardson et al. (2005)
dFnl	Change in financial liabilities	Richardson et al. (2005)
dBe	Change in common equity	Richardson et al. (2005)

Continued on next page

Table A1 – continued from previous page

Anomaly ID	Explanation	Original Paper
Dac	Discretionary accruals	Xie (2001)
POA	Percent operating accruals	Hafzalla et al. (2011)
Pta	Percent total accruals	Hafzalla et al. (2011)
Pda	Percent discretionary accruals	Hafzalla et al. (2011)
	Profitability	
RNA	Return on net operating assets	Soliman (2008)
PM	Profit margin	Soliman (2008)
ATO	Assets turnover	Soliman (2008)
Cto	Capital turnover	Haugen and Baker (1996)
Gpa	Gross profits-to-assets	Novy-Marx (2013)
Gla	Gross profits-to-lagged assets	Novy-Marx (2013)
Ope	Op. profits-to-book equity	Fama and French (2015)
Ole	Op. profits-to-lagged book equity	Fama and French (2015)
Opa	Op. profits-to-book assets	Ball et al. (2016)
Ola	Op. profits-to-lagged book assets	Ball et al. (2016)
CashOP	Cash-based op. profits-to-book	Ball et al. (2016)
CashOPl	Cash-based op. profits-to-lagged book assets	Ball et al. (2016)
O	Ohlson's (1980) O-score	Dichev (1998)
AltmanZ	Altmans (1968) Z-score	Dichev (1998)
Tbi	Taxable income-to-book income	Lev and Nissim (2004)
Bl	Book leverage	Fama and French (1992)
	Intangibles	
OCA	Org. capital-to-book assets	Eisfeldt and Papanikolaou (2013)
IOCA	Ind.-adj. org. capital-to-book assets	Eisfeldt and Papanikolaou (2013)
ADM	Advertising expense-to-market	Chan et al. (2001)
gAD	Growth in advertising expense	Lou (2014)
RDM	R&D expense-to-market	Chan et al. (2001)
RDS	R&D expense-to-sales	Chan et al. (2001)
OL	Operating leverage	Novy-Marx (2011)
HR	Hiring rate	Belo et al. (2014a)

Continued on next page

Table A1 – continued from previous page

Anomaly ID	Explanation	Original Paper
RCA	R&D capital-to-book assets	Li (2011)
BCA	Brand capital-to-book assets	Belo et al. (2014b)
dSi	Change in sales minus change in inventory	Abarbanell and Bushee (1998)
dSa	Change in sales minus change in accounts receivable	Abarbanell and Bushee (1998)
dGs	Change in gross margin minus change in sales	Abarbanell and Bushee (1998)
dSs	Change in sales minus change in SG&A	Abarbanell and Bushee (1998)
Etr	Effective tax rate	Abarbanell and Bushee (1998)
Lfe	Labor force efficiency	Abarbanell and Bushee (1998)
Tan	Tangibility of assets	Hahn and Lee (2009)
Rer	Real estate ratio	Tuzel (2010)
Kzi	KZ index of financing constraints	Lamont et al. (2001)
Wwi	Whited-Wu index of financing constraints	Whited and Wu (2006)
Sdd	Secured debt-to-total debt	Valta (2016)
OBA	Order backlog	Rajgopal et al. (2003)
Eper	Earnings persistence	Francis et al. (2004)
Eprd	Earnings predictability	Francis et al. (2004)
Esm	Earnings smoothness	Francis et al. (2004)
Evr	Value relevance of earnings	Francis et al. (2004)
Etl	Earnings timeliness	Francis et al. (2004)
Ecs	Earnings conservatism	Francis et al. (2004)
Frm	Pension funding rate to market equity	Franzoni and Marin (2006)
Fra	Pension funding rate to book assets	Franzoni and Marin (2006)
Ala	Liquidity of book assets	Ortiz-Molina and Phillips (2014)
Alm	Liquidity of market assets	Ortiz-Molina and Phillips (2014)
Ra1	Year 1-lagged return, annual	Heston and Sadka (2008)
Rn1	Year 1-lagged return, nonannual	Heston and Sadka (2008)
Ra2_5	Year 2-5 lagged return, annual	Heston and Sadka (2008)
Rn2_5	Year 2-5 lagged return, nonannual	Heston and Sadka (2008)
Ra6_10	Year 6-10 lagged return, annual	Heston and Sadka (2008)
Rn6_10	Year 6-10 lagged return, nonannual	Heston and Sadka (2008)

Table A2: OVIMS and conversion returns across anomalies
We show OVIMS, its t-value, bootstrapped 95%-confidence intervals, the effect size, non-normalized OVIMS, unconditional and conditional conversion returns for all anomalies that we consider in our analysis. We compute an anomaly's OVIMS as the difference in long-short returns calculated on high O/S stocks and calculated on low O/S stocks. We normalize this difference by the maximum average long-short return across the O/S quintiles, that is a measure of the effect size. We use 20.000 bootstrap iterations in the calculation of the confidence intervals. We adopt the anomaly categorization of Hou et al. (2020). We compute conversion returns at the first trading day of an option pair. The stock returns are calculated accordingly over the one month to maturity of that same option pair. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from March 1996 to December 2018.

Anomaly	Category	OVIMS	T-value	B.c.int	Effect	n.OVIMS	r^G_{unc}	r^G_{OS1}	r^G_{OS5}
PPS	Frictions	1.23	4.90	[0.78,1.90]	1.39	1.70	0.10	0.03	0.28
Rsix	Momentum	1.09	4.46	[0.65,1.76]	1.52	1.65	0.02	-0.02	0.11
Ami	Frictions	1.15	4.45	[0.71,1.86]	1.26	1.45	0.12	0.03	0.33
RNA	Profitability	1.23	4.00	[0.81,1.79]	1.17	1.44	0.05	0.02	0.13
Ole	Profitability	1.38	3.99	[0.88,1.93]	1.01	1.39	0.04	0.02	0.12
Dtv	Frictions	1.24	3.86	[0.75,1.89]	1.01	1.25	0.09	0.02	0.29
Ivol_Q	Frictions	0.91	3.83	[0.41,1.64]	1.31	1.19	0.11	0.01	0.29
Ivol_CAPM	Frictions	0.92	3.82	[0.45,1.73]	1.35	1.24	0.11	0.00	0.28
Ivol_FF3	Frictions	0.91	3.65	[0.43,1.72]	1.30	1.18	0.11	0.00	0.29
O	Profitability	1.07	3.46	[0.67,1.56]	1.16	1.25	0.07	0.02	0.16
Ope	Profitability	1.06	3.43	[0.62,1.74]	1.17	1.24	0.06	0.03	0.12
Gla	Profitability	1.03	3.22	[0.54,1.57]	1.06	1.09	0.04	0.03	0.08
Gpa	Profitability	0.86	3.22	[0.45,1.21]	1.29	1.10	0.05	0.05	0.10
Ndpq	Value	1.48	3.19	[0.70,1.94]	0.78	1.15	0.05	0.03	0.12
ME_June	Frictions	1.05	3.16	[0.49,1.79]	0.98	1.03	0.12	0.02	0.33
TVol	Frictions	0.89	3.02	[0.31,1.74]	1.16	1.03	0.10	0.01	0.26
Releven	Momentum	1.01	2.98	[0.39,1.74]	1.11	1.12	0.04	0.00	0.14
CashOP	Profitability	0.78	2.94	[0.34,1.07]	1.38	1.08	0.07	0.05	0.18
Ivol_AHT	Frictions	0.82	2.93	[0.32,1.75]	1.24	1.02	0.13	0.01	0.33
ATO	Profitability	0.98	2.90	[0.39,1.66]	0.84	0.82	0.02	0.02	0.05
Ebpq	Value	1.80	2.85	[0.48,1.94]	0.52	0.94	0.02	0.02	0.04
Rmom6	Momentum	0.99	2.77	[0.34,1.61]	0.83	0.82	0.01	-0.03	0.04
PM	Profitability	1.06	2.76	[0.37,1.77]	0.92	0.98	0.06	0.03	0.15

Continued on next page

Table A2 – continued from previous page

Anomaly	Category	OVIMS	T-value	B.c.int	Effect	n.OVIMS	r^G_{unc}	r^G_{OS1}	r^G_{OS5}
Beta_Market	Frictions	0.99	2.65	[0.29,1.85]	0.90	0.89	0.04	0.00	0.13
Cto	Profitability	0.95	2.64	[0.32,1.61]	0.83	0.79	0.02	0.02	0.01
SALEP	Value	1.00	2.62	[0.32,1.75]	0.78	0.79	0.01	-0.02	0.02
OL	Intangibles	1.06	2.53	[0.31,1.78]	0.73	0.77	-0.01	-0.01	-0.04
Mdr	Frictions	0.76	2.52	[0.17,1.60]	1.01	0.77	0.10	0.03	0.22
dCol	Investment	1.14	2.46	[0.23,1.68]	0.60	0.68	0.00	0.00	0.00
Rn1	Intangibles	0.85	2.35	[0.15,1.58]	1.01	0.86	0.01	-0.01	0.08
CashOPl	Profitability	0.71	2.31	[0.12,1.04]	1.17	0.83	0.07	0.04	0.17
Abr	Momentum	1.24	2.19	[0.13,1.79]	0.51	0.64	0.02	0.01	0.06
OBA	Intangibles	1.14	2.11	[0.10,1.81]	1.04	1.18	0.01	0.00	0.02
dFnl	Investment	0.81	2.11	[0.09,1.34]	0.71	0.58	0.02	0.01	0.04
Ola	Profitability	0.79	2.10	[0.04,1.40]	0.95	0.76	0.05	0.03	0.10
NPM	Value	0.91	2.01	[0.03,1.66]	0.71	0.65	0.03	0.03	0.07
Cei	Investment	0.69	2.00	[0.02,1.41]	0.85	0.59	0.04	0.02	0.08
RS	Momentum	0.84	1.94	[0.01,1.56]	0.71	0.60	0.04	0.02	0.06
EM	Value	0.93	1.92	[-0.05,1.66]	0.71	0.66	0.00	0.00	0.00
OA	Investment	1.89	1.92	[-0.03,1.94]	0.29	0.55	0.01	-0.01	-0.03
RDS	Intangibles	1.63	1.89	[-0.05,1.88]	0.50	0.82	0.03	0.00	0.08
OCFP	Value	0.90	1.78	[-0.09,1.69]	0.65	0.59	-0.01	-0.02	0.00
Rmom11	Momentum	0.65	1.78	[-0.09,1.21]	0.90	0.58	0.01	-0.01	0.05
Opa	Profitability	0.64	1.76	[-0.09,1.03]	1.01	0.64	0.06	0.03	0.13
dLti	Investment	1.32	1.75	[-0.12,1.87]	0.59	0.79	0.01	0.00	0.02
SUE	Momentum	1.35	1.73	[-0.16,1.86]	0.36	0.49	0.03	0.01	0.08
Noa	Investment	0.75	1.72	[-0.10,1.37]	0.66	0.50	0.01	0.01	0.03
dNco	Investment	0.47	1.71	[-0.06,1.06]	1.02	0.48	0.02	0.01	0.06
I.A	Investment	0.61	1.65	[-0.12,1.05]	0.84	0.51	0.01	-0.01	0.03
Ivc	Investment	0.97	1.62	[-0.20,1.60]	0.48	0.46	0.01	0.00	0.06
Etl	Intangibles	1.36	1.54	[-0.36,1.87]	0.33	0.45	0.00	0.03	-0.02
CVDtv	Frictions	0.97	1.53	[-0.26,1.67]	0.46	0.44	0.10	0.02	0.24
EP	Value	0.68	1.50	[-0.29,1.60]	0.74	0.50	-0.01	-0.01	-0.02
Eprd	Intangibles	0.46	1.47	[-0.19,0.87]	1.05	0.49	0.02	0.01	0.02
TS	Frictions	1.03	1.47	[-0.28,1.81]	0.38	0.39	0.02	0.02	0.01

Continued on next page

Table A2 – continued from previous page

Anomaly	Category	OVIMS	T-value	B.c.int	Effect	n.OVIMS	r^G_{unc}	r^G_{OS1}	r^G_{OS5}
Sm	Momentum	1.41	1.45	[-0.37,1.84]	0.50	0.70	0.00	0.01	-0.01
BCA	Intangibles	0.78	1.40	[-0.24,1.51]	0.86	0.67	0.00	0.06	-0.05
Wwi	Intangibles	0.99	1.33	[-0.47,1.76]	0.44	0.43	0.06	-0.01	0.19
dGs	Intangibles	1.03	1.33	[-0.41,1.72]	0.38	0.39	0.02	0.02	0.04
TAM	Value	1.01	1.30	[-0.43,1.62]	0.39	0.39	-0.01	-0.04	0.01
Ivg	Investment	0.67	1.25	[-0.33,1.24]	0.52	0.35	0.02	0.02	0.06
dNca	Investment	0.40	1.20	[-0.25,1.07]	0.86	0.34	0.01	0.00	0.04
TR	Frictions	1.03	1.19	[-0.55,1.78]	0.38	0.39	-0.02	-0.02	-0.06
SR	Value	0.96	1.08	[-0.57,1.62]	0.30	0.29	0.01	0.00	0.03
CV	Frictions	0.91	1.06	[-0.73,1.73]	0.35	0.32	0.09	0.02	0.22
CP	Value	0.67	1.05	[-0.70,1.54]	0.55	0.37	-0.02	-0.02	-0.04
Tbi	Profitability	0.79	1.02	[-0.57,1.62]	0.36	0.29	0.00	0.00	0.00
ADM	Intangibles	0.69	1.00	[-0.56,1.51]	0.72	0.50	-0.03	0.01	-0.07
Iskew_Q	Frictions	1.42	1.00	[-0.88,1.86]	0.19	0.27	0.02	0.00	0.02
Ra1	Intangibles	0.53	0.95	[-0.57,1.28]	0.54	0.29	-0.02	-0.01	-0.04
STR	Frictions	0.90	0.91	[-0.62,1.63]	0.32	0.29	-0.01	-0.02	0.02
BMa	Value	0.50	0.85	[-0.71,1.37]	0.54	0.27	0.00	-0.04	0.00
HR	Intangibles	0.28	0.85	[-0.44,1.07]	0.90	0.25	0.01	-0.02	0.05
Ra6_10	Intangibles	0.40	0.75	[-0.62,1.11]	0.58	0.23	0.01	0.02	0.01
Ala	Intangibles	0.62	0.73	[-0.82,1.36]	0.35	0.22	0.03	-0.02	0.06
TPM	Value	0.45	0.71	[-0.89,1.33]	0.51	0.23	0.00	0.01	0.00
IG	Investment	0.42	0.70	[-0.75,1.34]	0.51	0.21	0.00	-0.02	0.02
Lfe	Intangibles	0.54	0.70	[-0.73,1.31]	0.38	0.21	0.01	0.02	0.00
OCA	Intangibles	0.28	0.66	[-0.59,0.86]	0.75	0.21	0.04	0.02	0.07
dCoa	Investment	0.35	0.66	[-0.74,1.32]	0.55	0.19	0.00	0.00	0.02
Evr	Intangibles	1.22	0.65	[-1.07,1.72]	0.15	0.18	0.00	-0.02	0.00
EBP	Value	0.52	0.57	[-0.85,1.39]	0.34	0.18	-0.02	-0.03	-0.03
Kzi	Intangibles	0.52	0.57	[-0.98,1.53]	0.34	0.18	0.02	0.01	0.07
dNoa	Investment	0.17	0.56	[-0.45,0.86]	0.89	0.15	0.01	0.00	0.05
Ta	Investment	0.50	0.53	[-1.01,1.62]	0.33	0.17	0.01	0.01	0.01
dFin	Investment	0.22	0.52	[-0.76,1.09]	0.72	0.16	0.02	0.02	0.06
Ecs	Intangibles	0.40	0.45	[-1.15,1.49]	0.40	0.16	-0.01	-0.04	0.00

Continued on next page

Table A2 – continued from previous page

Anomaly	Category	OVIMS	T-value	B.c.int	Effect	n.OVIMS	r^G_{unc}	r^G_{OS1}	r^G_{OS5}
Iskew_CAPM	Frictions	0.35	0.45	[-1.04,1.39]	0.31	0.11	0.02	0.01	0.01
dPia	Investment	0.15	0.40	[-0.66,0.92]	0.77	0.12	0.02	0.01	0.05
Altman_Z	Profitability	0.41	0.39	[-1.02,1.49]	0.31	0.13	0.02	0.04	0.00
dSs	Intangibles	0.21	0.36	[-0.91,1.39]	0.57	0.12	0.00	0.01	0.00
Bl	Profitability	0.31	0.30	[-1.14,1.20]	0.30	0.09	0.00	0.00	0.03
RDM	Intangibles	0.13	0.20	[-0.82,1.18]	0.67	0.09	-0.01	0.01	0.01
dNcl	Investment	0.12	0.20	[-1.09,1.24]	0.46	0.05	0.00	0.00	-0.01
Pda	Investment	0.16	0.17	[-1.14,1.17]	0.29	0.05	0.01	0.00	0.04
dLno	Investment	0.06	0.17	[-0.65,0.73]	0.84	0.05	0.00	0.00	0.02
IOCA	Intangibles	0.07	0.16	[-0.89,0.84]	0.64	0.05	0.03	0.01	0.06
SG	Value	0.09	0.16	[-1.02,1.12]	0.52	0.05	0.01	0.00	0.03
Fra	Intangibles	0.07	0.13	[-0.97,1.03]	0.60	0.04	0.00	0.01	-0.03
Log_Growth_BD	Investment	0.13	0.13	[-1.28,1.12]	0.36	0.05	0.02	0.02	0.03
TDM	Value	0.08	0.11	[-1.11,0.89]	0.45	0.03	0.00	-0.03	0.02
Esm	Intangibles	0.22	0.07	[-1.53,1.53]	0.11	0.02	0.00	0.00	0.00
SVR	Frictions	0.05	0.06	[-1.20,0.89]	0.41	0.02	0.01	0.00	0.04
dBe	Investment	0.03	0.05	[-0.92,0.77]	0.60	0.02	0.00	-0.01	-0.01
gAD	Intangibles	-0.03	-0.02	[-1.49,1.48]	0.40	-0.01	0.02	-0.04	0.03
IG2	Investment	-0.04	-0.06	[-1.23,1.00]	0.49	-0.02	0.00	-0.02	0.01
dIi	Investment	-0.03	-0.06	[-1.03,0.83]	0.61	-0.02	0.00	-0.02	0.04
Rn6_10	Intangibles	-0.04	-0.07	[-0.94,0.87]	0.67	-0.02	0.00	0.00	0.01
dWc	Investment	-0.06	-0.07	[-1.40,1.39]	0.35	-0.02	0.00	0.00	0.06
Beta_Dimson	Frictions	-0.22	-0.08	[-1.43,1.33]	0.12	-0.03	-0.02	-0.01	-0.03
Alm	Intangibles	-0.05	-0.09	[-1.43,1.02]	0.51	-0.03	0.02	-0.01	0.05
Iadj_Rer	Intangibles	-0.07	-0.10	[-1.47,1.20]	0.51	-0.04	0.03	0.02	0.07
RCA	Intangibles	-0.11	-0.12	[-1.18,1.01]	0.50	-0.05	0.00	0.02	-0.03
Epq	Value	-0.11	-0.17	[-1.44,0.81]	0.52	-0.06	0.00	0.00	-0.03
Sdd	Intangibles	-0.11	-0.17	[-1.32,1.13]	0.61	-0.07	-0.03	-0.01	-0.05
TES	Momentum	-0.65	-0.17	[-1.64,1.44]	0.08	-0.05	0.02	0.00	0.02
beta.BD.lev	Frictions	-0.17	-0.32	[-1.37,0.79]	0.66	-0.11	0.00	0.02	-0.03
BMJ	Value	-0.23	-0.33	[-1.58,0.83]	0.46	-0.11	-0.01	-0.03	-0.02
Iskew_FF3	Frictions	-0.64	-0.36	[-1.66,1.18]	0.14	-0.09	-0.02	-0.02	-0.01

Continued on next page

Table A2 – continued from previous page

Anomaly	Category	OVIMS	T-value	B.c.int	Effect	n.OVIMS	r^G_{unc}	r^G_{OS1}	r^G_{OS5}
PS_Beta	Frictions	-0.58	-0.49	[-1.61,1.14]	0.29	-0.17	0.00	-0.02	0.01
Emq	Value	-0.36	-0.50	[-1.59,0.68]	0.50	-0.18	0.01	0.02	-0.01
dSti	Investment	-0.43	-0.54	[-1.63,0.96]	0.60	-0.26	0.01	0.03	0.01
Frm	Intangibles	-0.42	-0.56	[-1.35,0.78]	0.46	-0.20	-0.02	-0.01	-0.07
Dac	Investment	-0.68	-0.57	[-1.74,1.02]	0.25	-0.17	0.00	0.00	0.04
Rn2_5	Intangibles	-0.38	-0.57	[-1.62,0.64]	0.52	-0.20	-0.01	-0.02	0.00
Tur	Frictions	-0.30	-0.61	[-1.46,0.52]	0.65	-0.20	0.05	-0.01	0.14
Tan	Intangibles	-0.96	-0.66	[-1.71,0.92]	0.21	-0.20	0.02	-0.02	0.07
Spq	Value	-0.35	-0.67	[-1.65,0.50]	0.65	-0.22	0.00	-0.01	0.00
Pta	Investment	-0.77	-0.70	[-1.76,0.92]	0.28	-0.21	-0.01	-0.02	0.01
Ra2_5	Intangibles	-0.64	-0.75	[-1.61,0.78]	0.37	-0.24	0.00	0.02	0.00
Etr	Intangibles	-0.66	-0.81	[-1.59,0.72]	0.37	-0.24	0.00	-0.01	-0.01
Cpq	Value	-0.54	-0.86	[-1.65,0.50]	0.50	-0.27	-0.01	-0.01	-0.04
Dmq	Value	-0.73	-0.88	[-1.64,0.53]	0.41	-0.30	-0.02	-0.03	-0.02
dSa	Intangibles	-1.10	-0.90	[-1.75,1.00]	0.24	-0.26	0.01	0.00	0.02
POA	Investment	-0.73	-1.01	[-1.63,0.55]	0.40	-0.29	0.02	0.00	0.06
IG3	Investment	-0.78	-1.13	[-1.73,0.50]	0.45	-0.35	0.01	-0.01	0.00
Eper	Intangibles	-1.18	-1.20	[-1.76,0.57]	0.33	-0.39	0.00	-0.02	0.00
LTR	Value	-0.96	-1.28	[-1.81,0.37]	0.47	-0.45	-0.04	-0.04	-0.07
dSi	Intangibles	-1.98	-1.39	[-1.92,0.58]	0.23	-0.45	0.00	0.00	0.01
Coskw	Frictions	-1.39	-1.40	[-1.86,0.46]	0.29	-0.40	-0.01	-0.01	0.01
Ocpq	Value	-1.01	-1.45	[-1.83,0.26]	0.56	-0.56	-0.04	-0.02	-0.09
Amq	Value	-1.09	-1.62	[-1.75,0.18]	0.46	-0.51	0.00	-0.01	-0.01
AvgCE	Investment	-1.73	-1.85	[-1.94,0.07]	0.34	-0.59	-0.01	-0.02	-0.04
NDP	Value	-1.31	-2.11	[-1.84,-0.07]	0.57	-0.74	-0.05	-0.04	-0.10

Table A3: Regressions of conversion returns on LSOI for mispricing anomalies

We regress a mispricing anomaly's long-short conversion return on its long-short option order imbalance. Specifically, we estimate the following model: $r^G_{a,t} = \alpha_{a,j} + \beta_{a,j} LSOI_{a,j,t} + \epsilon_{a,j,t}$, where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile in month t, and $LSOI_{a,j,t}$ is the long-short option order imbalance measure of trader type j, calculated over the same portfolios as $r^G_{a,t}$, in month t. For each mispricing anomaly, we estimate time series regressions for each trader type. Cust, ProC, BD, Prop and MM denote the regressions of trader type customer, professional customer, broker-dealer, proprietary trader and market maker. We compute conversion returns at the first trading day of an option pair. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. T-statistics are calculated using Newey and West (1987) standard errors. The sample covers the period from May 2005 to December 2018. The time series pertaining to professional customers starts from October 2009.

Anomaly	Category	OVIMS	B.c.int	β_{Cust}	t	β_{ProC}	t	β_{BD}	t	β_{Prop}	t	β_{MM}	t
PPS	Frictions	1.23	[0.78,1.90]	0.00	0.01	0.29	1.05	-0.34	-1.18	-0.06	-0.42	0.01	0.20
Rsix	Momentum	1.09	[0.65,1.76]	0.02	0.38	0.38	1.33	-0.06	-0.22	0.30	2.92	-0.08	-1.50
Ami	Frictions	1.15	[0.71,1.86]	-0.05	-0.62	0.21	0.51	-0.01	-0.03	-0.32	-1.80	0.11	1.29
RNA	Profitability	1.23	[0.81,1.79]	-0.01	-0.26	0.09	1.18	0.01	0.03	-0.06	-0.42	0.01	0.25
Ole	Profitability	1.38	[0.88,1.93]	0.00	-0.05	-0.10	-0.43	0.26	1.14	0.06	0.54	-0.02	-0.59
Dtv	Frictions	1.24	[0.75,1.89]	-0.08	-1.20	0.26	0.51	-0.44	-1.56	-0.05	-0.35	0.13	1.68
Ivol_Q	Frictions	0.91	[0.41,1.64]	-0.07	-0.80	-0.20	-0.53	0.41	1.17	0.27	1.43	-0.01	-0.10
Ivol_CAPM	Frictions	0.92	[0.45,1.73]	-0.03	-0.32	-0.34	-0.89	0.14	0.41	0.29	1.69	-0.02	-0.21
Ivol_FF3	Frictions	0.91	[0.43,1.72]	-0.07	-0.73	-0.26	-0.68	0.33	0.82	0.39	2.06	-0.03	-0.30
O	Profitability	1.07	[0.67,1.56]	-0.05	-1.06	0.20	0.74	0.19	0.74	0.16	1.55	0.01	0.16
Ope	Profitability	1.06	[0.62,1.74]	0.00	0.02	-0.03	-0.11	0.27	1.40	0.15	1.65	-0.05	-1.21
Gla	Profitability	1.03	[0.54,1.57]	0.12	1.89	0.04	0.26	0.17	0.70	-0.01	-0.13	-0.13	-1.88
Gpa	Profitability	0.86	[0.45,1.21]	0.09	1.61	0.11	0.37	0.31	0.92	-0.01	-0.08	-0.11	-1.64
Ndpq	Value	1.48	[0.70,1.94]	0.03	0.66	-0.13	-0.73	-0.27	-1.02	0.12	0.96	-0.04	-0.90
ME_June	Frictions	1.05	[0.49,1.79]	-0.02	-0.31	0.13	0.45	-0.20	-0.66	-0.46	-1.92	0.12	1.33
TVol	Frictions	0.89	[0.31,1.74]	-0.03	-0.43	-0.26	-0.79	0.32	1.20	0.11	0.82	0.00	0.02

Continued on next page

Table A3 – continued from previous page

Anomaly	Category	OVIMS	B.c.int	β_{Cust}	t	β_{ProC}	t	β_{BD}	t	β_{Prop}	t	β_{MM}	t
Releven	Momentum	1.01	[0.39,1.74]	-0.03	-0.63	-0.15	-0.46	0.40	1.39	0.50	3.56	-0.06	-1.35
CashOP	Profitability	0.78	[0.34,1.07]	-0.04	-0.79	-0.52	-1.80	0.35	1.29	0.14	1.23	0.01	0.26
Ivol_AHT	Frictions	0.82	[0.32,1.75]	-0.07	-0.73	-0.19	-0.53	0.24	0.66	0.35	1.67	0.01	0.09
ATO	Profitability	0.98	[0.39,1.66]	0.14	2.07	0.19	0.82	0.14	0.66	-0.09	-0.90	-0.13	-2.07
Ebpq	Value	1.80	[0.48,1.94]	-0.05	-0.71	0.22	0.58	0.10	0.43	-0.13	-0.98	0.06	1.07
Rmom6	Momentum	0.99	[0.34,1.61]	0.02	0.44	-0.28	-1.43	0.12	1.19	0.14	1.49	-0.04	-0.68
PM	Profitability	1.06	[0.37,1.77]	-0.05	-0.98	-0.40	-1.62	0.15	0.65	0.21	2.32	0.01	0.36
Beta_Market	Frictions	0.99	[0.29,1.85]	-0.02	-0.52	0.61	3.81	-0.06	-0.22	0.05	0.40	0.00	-0.09
Cto	Profitability	0.95	[0.32,1.61]	0.09	1.41	0.45	2.14	-0.28	-1.29	0.25	1.38	-0.15	-1.76
SALEP	Value	1.00	[0.32,1.75]	0.00	-0.06	0.28	1.46	0.15	0.63	0.22	1.96	-0.07	-1.60
OL	Intangibles	1.06	[0.31,1.78]	0.10	2.04	0.14	0.78	-0.18	-1.11	-0.02	-0.17	-0.10	-1.67
Mdr	Frictions	0.76	[0.17,1.60]	-0.06	-0.94	-0.43	-1.23	0.19	0.90	0.21	1.92	0.03	0.48
dCol	Investment	1.14	[0.23,1.68]	0.05	1.22	-0.04	-0.19	0.00	-0.02	-0.06	-0.67	-0.04	-0.92
Rn1	Intangibles	0.85	[0.15,1.58]	0.02	0.35	0.34	1.42	0.02	0.09	0.33	2.63	-0.09	-1.75
CashOPl	Profitability	0.71	[0.12,1.04]	-0.01	-0.11	-0.43	-1.65	0.19	0.67	0.10	0.75	-0.01	-0.13
Abr	Momentum	1.24	[0.13,1.79]	0.01	0.37	-0.18	-0.80	0.51	2.07	0.03	0.40	-0.04	-0.74
OBA	Intangibles	1.14	[0.10,1.81]	0.00	0.11	0.10	0.72	-0.20	-1.59	-0.06	-0.68	0.03	0.96
dFnl	Investment	0.81	[0.09,1.34]	0.01	0.21	0.34	2.38	-0.19	-1.09	-0.02	-0.22	-0.01	-0.39
Ola	Profitability	0.79	[0.04,1.40]	-0.01	-0.11	-0.01	-0.03	0.36	1.19	0.04	0.31	-0.02	-0.32
NPM	Value	0.91	[0.03,1.66]	-0.09	-1.87	0.38	1.81	0.12	0.47	0.20	1.84	0.04	1.06
Cei	Investment	0.69	[0.02,1.41]	0.00	0.08	0.45	2.82	0.00	0.00	0.12	1.33	-0.05	-1.21
RS	Momentum	0.84	[0.01,1.56]	-0.02	-0.67	0.54	2.30	0.17	1.01	0.06	0.83	-0.03	-0.80

Table A4: Regressions of conversion returns on frictions for mispricing anomalies

For each mispricing anomaly we estimate the following model: $r^G_{a,t} = \alpha_a + \beta_{a,sf} SF_{t-1} + \beta_{a,bas} BAS_{t-1} + \beta_{a,bao} BAO_{t-1} + \beta_{a,icr} ICR_{t-1} + \beta_{a,ted} TED_{t-1} + r^G_{a,t-1} + \epsilon_{a,t}$, where $r^G_{a,t}$ is the conversion long-short return of mispricing anomaly a in the top O/S quintile in month t, SF_{t-1} is the cross-sectional average shorting fee, BAS_{t-1} is the cross-sectional average stock bid-ask spread, BAO_{t-1} is the volume-weighted cross-sectional average call option bid-ask spread, ICR_{t-1} is the intermediary capital ratio, TED_{t-1} is the TED spread and $r^G_{a,t-1}$ is the conversion long-short return of mispricing anomaly a, all measured at the end of month $t-1$. We compute equally weighted conversion returns at the first trading day of an option pair. T-statistic are calculated using Newey and West (1987) standard errors. Estimates are displayed in percent. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from August 2006 to December 2018.

Anomaly	Category	OVIMS	B.c.int	β_{SF}	t	β_{BAS}	t	β_{TED}	t	β_{ICR}	t	β_{BAO}	t	β_{Lag}	t	R^2
PPS	Frictions	1.23	[0.78,1.9]	0.14	5.80	0.06	1.75	-0.06	-1.50	0.01	0.28	-0.01	-0.54	11.35	1.68	30.18
Rsix	Momentum	1.09	[0.65,1.76]	0.06	3.78	0.03	0.69	-0.04	-1.19	-0.01	-0.54	0.02	1.19	25.61	3.05	14.93
Ami	Frictions	1.15	[0.71,1.86]	0.15	5.58	0.09	2.59	-0.03	-1.02	-0.01	-0.36	-0.02	-0.89	11.06	1.50	36.56
RNA	Profitability	1.23	[0.81,1.79]	0.05	2.63	0.05	1.47	-0.05	-1.55	0.06	2.14	-0.04	-1.22	21.00	2.58	15.65
Ole	Profitability	1.38	[0.88,1.93]	0.05	2.65	0.06	1.89	-0.07	-2.05	0.06	2.80	-0.03	-1.48	24.99	2.60	20.04
Dtv	Frictions	1.24	[0.75,1.89]	0.13	5.17	0.06	1.75	-0.02	-0.54	-0.03	-1.08	-0.01	-0.45	8.01	0.81	34.40
Ivol_Q	Frictions	0.91	[0.41,1.64]	0.16	8.04	0.07	1.91	-0.03	-0.67	0.00	-0.16	0.01	0.39	2.97	0.37	32.20
Ivol_CAPM	Frictions	0.92	[0.45,1.73]	0.15	8.16	0.07	1.45	-0.01	-0.19	0.00	-0.07	0.00	-0.12	4.02	0.57	30.89
Ivol_FF3	Frictions	0.91	[0.43,1.72]	0.15	6.94	0.10	2.77	-0.04	-1.02	0.00	0.10	0.00	-0.12	3.12	0.37	31.15
O	Profitability	1.07	[0.67,1.56]	0.06	2.71	0.08	2.48	-0.07	-2.70	0.03	1.19	-0.03	-0.95	6.08	0.68	13.65
Ope	Profitability	1.06	[0.62,1.74]	0.04	2.16	0.03	0.87	-0.03	-1.84	0.03	1.42	-0.02	-1.41	15.05	1.76	7.00
Gla	Profitability	1.03	[0.54,1.57]	0.05	2.24	0.05	1.55	-0.11	-3.15	0.07	2.94	-0.05	-1.71	20.50	2.28	33.59
Gpa	Profitability	0.86	[0.45,1.21]	0.05	1.98	0.05	1.14	-0.09	-3.17	0.05	1.71	-0.04	-1.05	19.46	2.15	22.89
Ndpq	Value	1.48	[0.7,1.94]	-0.03	-0.71	0.12	2.35	-0.11	-1.67	0.05	1.49	-0.08	-1.68	10.05	0.99	14.86
ME_June	Frictions	1.05	[0.49,1.79]	0.16	5.89	0.08	2.37	-0.01	-0.60	-0.01	-0.38	-0.01	-0.33	10.78	1.23	39.80
TVol	Frictions	0.89	[0.31,1.74]	0.13	5.47	0.05	1.45	-0.06	-1.71	0.00	0.01	0.01	0.22	1.09	0.13	18.97

Continued on next page

Table A4 – continued from previous page

Anomaly	Category	OVIMS	B.c.int	β_{SF}	t	β_{BAS}	t	β_{TED}	t	β_{ICR}	t	β_{BAO}	t	β_{Lag}	t	R^2
Releven	Momentum	1.01	[0.39,1.74]	0.10	4.07	0.02	0.77	-0.01	-0.41	-0.03	-0.86	0.04	1.56	16.39	1.63	23.80
CashOP	Profitability	0.78	[0.34,1.07]	0.08	4.32	0.04	1.40	-0.04	-1.67	0.00	0.11	-0.01	-0.64	6.76	0.79	14.50
Ivol_AHT	Frictions	0.82	[0.32,1.75]	0.17	6.87	0.07	1.80	-0.05	-1.60	-0.01	-0.48	0.00	0.00	14.16	1.63	39.57
ATO	Profitability	0.98	[0.39,1.66]	0.04	2.29	0.03	0.77	-0.07	-1.99	0.05	2.31	-0.04	-1.15	11.97	1.19	19.86
Ebpq	Value	1.80	[0.48,1.94]	0.06	2.46	0.10	2.75	-0.09	-3.01	0.03	1.10	-0.02	-0.86	30.35	3.44	26.44
Rmom6	Momentum	0.99	[0.34,1.61]	0.03	1.95	0.00	-0.24	0.01	0.66	-0.02	-0.93	0.01	0.51	26.65	5.39	13.32
PM	Profitability	1.06	[0.37,1.77]	0.06	2.47	0.06	1.63	-0.04	-1.60	0.03	1.23	-0.02	-0.98	15.50	1.78	13.73
Beta_Market	Frictions	0.99	[0.29,1.85]	0.08	5.37	0.04	1.93	-0.02	-1.17	0.01	0.68	0.00	-0.30	27.41	4.85	27.23
Cto	Profitability	0.95	[0.32,1.61]	0.03	1.26	0.03	1.09	-0.12	-3.50	0.06	2.89	-0.04	-1.60	16.32	1.83	45.05
SALEP	Value	1.00	[0.32,1.75]	0.02	0.94	-0.02	-0.41	-0.03	-0.91	-0.02	-0.75	0.00	0.03	2.39	0.25	1.08
OL	Intangibles	1.06	[0.31,1.78]	0.02	0.82	0.01	0.55	-0.09	-3.53	0.02	0.86	-0.01	-0.27	18.73	1.68	35.62
Mdr	Frictions	0.76	[0.17,1.6]	0.13	8.86	0.05	1.07	-0.04	-1.07	0.00	0.05	0.01	0.62	5.05	0.57	26.33
dCol	Investment	1.14	[0.23,1.68]	0.00	0.10	-0.03	-1.46	0.06	2.61	-0.03	-1.80	0.03	2.18	7.63	0.91	12.29
Rn1	Intangibles	0.85	[0.15,1.58]	0.04	2.24	0.02	0.73	-0.02	-0.68	-0.02	-0.98	0.05	2.35	28.24	2.42	16.77
CashOPl	Profitability	0.71	[0.12,1.04]	0.07	4.26	0.04	1.31	-0.05	-2.05	0.01	0.46	-0.01	-0.75	6.48	0.75	13.01
Abr	Momentum	1.24	[0.13,1.79]	0.03	1.35	0.03	1.02	-0.06	-1.81	0.02	0.81	0.02	1.20	20.19	2.66	7.21
OBA	Intangibles	1.14	[0.1,1.81]	0.00	0.11	-0.05	-1.15	-0.02	-0.65	-0.06	-1.05	0.04	0.91	13.67	1.30	1.89
dFnl	Investment	0.81	[0.09,1.34]	0.04	2.10	0.00	-0.14	0.04	1.38	-0.02	-0.65	0.01	0.38	34.18	3.92	24.82
Ola	Profitability	0.79	[0.04,1.4]	0.06	3.01	0.05	1.29	-0.08	-2.62	0.03	1.11	-0.02	-0.70	9.53	0.86	16.29
NPM	Value	0.91	[0.03,1.66]	0.09	5.92	0.00	0.04	-0.03	-1.35	0.00	-0.08	0.03	1.73	11.41	1.36	21.85
Cei	Investment	0.69	[0.02,1.41]	0.03	1.93	0.02	0.83	-0.04	-1.91	0.01	0.37	-0.02	-0.92	27.35	4.07	12.59
RS	Momentum	0.84	[0.01,1.56]	0.01	0.57	0.01	0.76	-0.03	-1.28	0.01	0.83	0.04	2.14	27.80	3.23	12.20

Table A5: OTM-OVIMS across anomalies

To investigate whether our results are robust when considering only out-of-the-money option volume, we calculate a stock's O/S as the out-of-the-money option-to-stock volume. We calculate $OVIMS$ for each anomaly that we consider in our analysis. We compute an anomaly's $OVIMS$ as the difference in long-short returns calculated on high O/S stocks and calculated on low O/S stocks. We normalize this difference by the maximum average long-short return across the O/S quintiles, that is a measure of the effect size. We report standard errors, t-values and bootstrapped confidence intervals of the mean. Specifically, we report 95% confidence intervals and use 20.000 iterations for the bootstrap. We adopt the anomaly categorization of Hou et al. (2020). All characteristics are signed so that a quintile portfolio sort results in a positive long-short return on our sample. We compute monthly stock returns from option maturity to option maturity. The sample we consider consists only of optionable stocks. We exclude financial firms and firms with negative book equity. The sample covers the period from March 1996 to December 2018.

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
PPS	Frictions	1.12	0.27	4.09	[0.65,1.86]
Ivol_FF3	Frictions	0.92	0.23	4.05	[0.53,1.65]
Rsix	Momentum	1.18	0.30	3.96	[0.57,1.84]
O	Profitability	1.10	0.29	3.77	[0.71,1.57]
Ivol_Q	Frictions	0.90	0.25	3.66	[0.42,1.62]
Ivol_CAPM	Frictions	0.88	0.24	3.64	[0.47,1.65]
Ole	Profitability	1.17	0.32	3.64	[0.71,1.85]
dNco	Investment	1.28	0.37	3.48	[0.62,1.85]
RNA	Profitability	1.15	0.33	3.47	[0.67,1.74]
Gpa	Profitability	0.99	0.29	3.43	[0.53,1.41]
Ebpq	Value	1.47	0.44	3.31	[0.71,1.94]
Noa	Investment	1.18	0.37	3.20	[0.54,1.83]
CashOP	Profitability	0.81	0.26	3.19	[0.37,1.09]
OL	Intangibles	1.30	0.43	2.99	[0.49,1.90]
OBA	Intangibles	1.15	0.39	2.97	[0.57,1.77]
ATO	Profitability	1.07	0.37	2.88	[0.39,1.77]
I_A	Investment	1.18	0.42	2.84	[0.48,1.83]
dNca	Investment	1.31	0.46	2.82	[0.37,1.82]
BCA	Intangibles	1.63	0.59	2.78	[0.48,1.94]
TVol	Frictions	0.91	0.33	2.78	[0.28,1.72]
Abr	Momentum	1.00	0.36	2.75	[0.43,1.63]
Ope	Profitability	1.01	0.37	2.75	[0.39,1.72]
Ami	Frictions	1.04	0.38	2.74	[0.33,1.84]

Continued on next page

Table A5 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
dCol	Investment	1.77	0.67	2.65	[0.47,1.95]
RDS	Intangibles	1.67	0.65	2.56	[0.35,1.93]
RS	Momentum	0.93	0.36	2.55	[0.30,1.49]
Beta_Market	Frictions	0.97	0.38	2.52	[0.25,1.84]
CashOPl	Profitability	0.77	0.31	2.52	[0.22,1.12]
ME_June	Frictions	1.13	0.45	2.52	[0.30,1.89]
NPM	Value	1.00	0.40	2.49	[0.29,1.75]
OA	Investment	1.81	0.74	2.47	[0.4,1.96]
Rmom6	Momentum	1.19	0.48	2.45	[0.27,1.84]
Gla	Profitability	0.98	0.40	2.44	[0.25,1.60]
Cei	Investment	0.89	0.37	2.43	[0.17,1.59]
Rn1	Intangibles	0.87	0.37	2.39	[0.22,1.76]
SALEP	Value	1.00	0.43	2.36	[0.19,1.75]
Cto	Profitability	1.03	0.45	2.31	[0.22,1.81]
dPia	Investment	1.26	0.55	2.28	[0.17,1.83]
PM	Profitability	1.01	0.45	2.25	[0.20,1.77]
SVR	Frictions	1.05	0.47	2.24	[0.19,1.68]
dNoa	Investment	1.13	0.51	2.22	[0.09,1.72]
Ivol_AHT	Frictions	0.76	0.34	2.21	[0.10,1.69]
Releven	Momentum	0.95	0.44	2.19	[0.14,1.79]
dLti	Investment	1.15	0.53	2.16	[0.11,1.90]
Dtv	Frictions	1.08	0.51	2.12	[0.11,1.85]
Ivc	Investment	1.40	0.70	2.01	[0.04,1.90]
OCA	Intangibles	0.62	0.31	2.00	[0.00,1.34]
Opa	Profitability	0.78	0.39	2.00	[0.01,1.21]
Ivg	Investment	1.14	0.58	1.96	[0.01,1.80]
dFnl	Investment	0.77	0.39	1.95	[0.00,1.63]
EM	Value	1.17	0.60	1.93	[-0.02,1.84]
EP	Value	1.21	0.63	1.92	[-0.06,1.87]
Eprd	Intangibles	0.55	0.29	1.90	[-0.01,0.98]
STR	Frictions	1.63	0.87	1.87	[-0.04,1.87]
Mdr	Frictions	0.51	0.29	1.74	[-0.07,1.25]

Continued on next page

Table A5 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
SUE	Momentum	1.15	0.66	1.74	[-0.13,1.86]
Ndpq	Value	1.93	1.13	1.72	[-0.16,1.87]
dFin	Investment	0.98	0.58	1.69	[-0.15,1.74]
dCoa	Investment	1.24	0.75	1.64	[-0.22,1.87]
Wwi	Intangibles	1.13	0.70	1.61	[-0.23,1.80]
Rmom11	Momentum	0.68	0.43	1.56	[-0.22,1.27]
Etl	Intangibles	1.30	0.84	1.55	[-0.30,1.83]
Ola	Profitability	0.68	0.44	1.55	[-0.19,1.26]
TS	Frictions	0.78	0.53	1.47	[-0.23,1.67]
TPM	Value	0.84	0.58	1.45	[-0.44,1.55]
SR	Value	0.77	0.55	1.40	[-0.30,1.32]
Sm	Momentum	1.04	0.80	1.31	[-0.59,1.81]
dLno	Investment	0.64	0.49	1.30	[-0.29,1.31]
CVDtv	Frictions	1.22	0.96	1.28	[-0.53,1.83]
Iadj_Rer	Intangibles	1.02	0.81	1.26	[-0.55,1.74]
Ra6_10	Intangibles	0.72	0.57	1.25	[-0.48,1.48]
Sdd	Intangibles	1.01	0.81	1.24	[-0.44,1.78]
Ta	Investment	1.94	1.56	1.24	[-0.66,1.89]
TR	Frictions	1.37	1.14	1.21	[-0.56,1.82]
gAD	Intangibles	1.48	1.22	1.21	[-0.66,1.85]
dBe	Investment	0.60	0.50	1.20	[-0.50,1.22]
HR	Intangibles	0.65	0.58	1.12	[-0.51,1.59]
dSs	Intangibles	0.79	0.71	1.11	[-0.62,1.73]
IOCA	Intangibles	0.50	0.46	1.10	[-0.40,1.29]
OCFP	Value	0.49	0.45	1.09	[-0.48,1.46]
dNcl	Investment	0.53	0.49	1.07	[-0.47,1.52]
ADM	Intangibles	1.09	1.03	1.06	[-0.75,1.80]
Ala	Intangibles	0.82	0.80	1.02	[-0.80,1.62]
CP	Value	0.79	0.77	1.02	[-0.80,1.63]
IG	Investment	0.64	0.67	0.95	[-0.60,1.61]
Tbi	Profitability	0.76	0.91	0.84	[-0.71,1.65]
Tur	Frictions	0.49	0.59	0.83	[-0.75,1.34]

Continued on next page

Table A5 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
BMa	Value	0.43	0.53	0.82	[-0.77,1.37]
SG	Value	0.43	0.52	0.82	[-0.54,1.31]
Kzi	Intangibles	0.90	1.14	0.80	[-1.02,1.65]
Iskew_Q	Frictions	0.80	1.02	0.79	[-0.79,1.70]
Ra1	Intangibles	0.44	0.56	0.79	[-0.73,1.20]
Ecs	Intangibles	0.83	1.08	0.77	[-0.98,1.56]
Evr	Intangibles	0.59	0.87	0.68	[-0.99,1.65]
Ra2_5	Intangibles	0.96	1.67	0.58	[-1.26,1.73]
RCA	Intangibles	0.42	0.86	0.49	[-0.92,1.42]
CV	Frictions	0.39	1.02	0.39	[-1.18,1.59]
Esm	Intangibles	0.39	1.37	0.29	[-1.37,1.58]
Beta_Dimson	Frictions	0.43	1.54	0.28	[-1.15,1.57]
RDM	Intangibles	0.19	0.69	0.27	[-0.82,1.22]
Iskew_CAPM	Frictions	0.20	0.76	0.26	[-1.13,1.43]
Lfe	Intangibles	0.27	1.24	0.22	[-1.30,1.29]
dIi	Investment	0.13	0.59	0.22	[-0.96,1.08]
Alm	Intangibles	0.18	0.84	0.21	[-1.33,1.25]
dGs	Intangibles	0.16	0.93	0.17	[-1.30,1.07]
Altman_Z	Profitability	0.17	1.17	0.15	[-1.31,1.47]
AvgCE	Investment	0.09	0.68	0.14	[-1.18,1.27]
IG2	Investment	0.08	0.62	0.14	[-0.96,1.09]
Rn2_5	Intangibles	0.16	1.27	0.13	[-1.47,1.20]
Epq	Value	0.07	0.60	0.11	[-1.22,0.88]
TDM	Value	0.11	1.25	0.09	[-1.44,1.27]
dSa	Intangibles	0.10	1.16	0.09	[-1.15,1.48]
dSti	Investment	0.09	2.73	0.03	[-1.54,1.62]
TAM	Value	0.02	1.11	0.02	[-1.51,1.21]
Fra	Intangibles	-0.09	1.10	-0.09	[-1.41,1.18]
Log_Growth_BD	Investment	-0.10	0.83	-0.12	[-1.56,1.23]
beta.BD.lev	Frictions	-0.18	0.63	-0.29	[-1.47,0.95]
Frm	Intangibles	-0.31	0.95	-0.33	[-1.54,1.03]
Rn6_10	Intangibles	-0.33	0.87	-0.37	[-1.60,1.11]

Continued on next page

Table A5 – continued from previous page

Anomaly	Category	OVIMS	Se(OVIMS)	T-value	Boots. confidence interval
Bl	Profitability	-0.40	0.80	-0.50	[-1.56,0.84]
LTR	Value	-0.82	1.63	-0.50	[-1.75,1.22]
Pta	Investment	-0.55	1.05	-0.52	[-1.56,0.92]
BMJ	Value	-0.46	0.78	-0.59	[-1.67,0.67]
Emq	Value	-0.40	0.63	-0.63	[-1.66,0.56]
Cpq	Value	-0.52	0.78	-0.66	[-1.70,0.58]
Spq	Value	-0.39	0.59	-0.66	[-1.67,0.52]
dSi	Intangibles	-1.24	1.78	-0.70	[-1.79,1.08]
IG3	Investment	-0.53	0.72	-0.73	[-1.61,0.83]
Etr	Intangibles	-0.53	0.66	-0.81	[-1.68,0.82]
EBP	Value	-1.12	1.26	-0.89	[-1.72,0.75]
Pda	Investment	-0.78	0.83	-0.94	[-1.73,0.64]
TES	Momentum	-0.93	0.94	-0.98	[-1.78,0.66]
Coskw	Frictions	-0.86	0.80	-1.07	[-1.72,0.60]
PS_Beta	Frictions	-0.76	0.72	-1.07	[-1.64,0.47]
Tan	Intangibles	-1.35	1.26	-1.07	[-1.78,0.64]
dWc	Investment	-0.65	0.54	-1.20	[-1.67,0.43]
POA	Investment	-0.86	0.67	-1.29	[-1.74,0.42]
Eper	Intangibles	-1.18	0.85	-1.38	[-1.72,0.38]
Iskew_FF3	Frictions	-1.39	1.00	-1.38	[-1.90,0.50]
Dac	Investment	-1.55	1.04	-1.49	[-1.91,0.38]
NDP	Value	-1.69	1.09	-1.54	[-1.88,0.30]
Ocpq	Value	-1.01	0.57	-1.78	[-1.85,0.10]
Dmq	Value	-1.48	0.81	-1.82	[-1.86,0.07]
Amq	Value	-1.86	0.71	-2.62	[-1.94,-0.35]

References

Abarbanell, J.S., Bushee, B.J., 1998. Abnormal returns to a fundamental analysis strategy. Accounting Review , 19–45.

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. The Journal of Finance 69, 2557–2596.

Ali, A., Hwang, L.S., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355–373.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets 5, 31–56.

Anderson, C.W., Garcia-Feijóo, L., 2006. Empirical evidence on capital investment, growth options, and security returns. The Journal of Finance 61, 171–194.

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. The review of financial studies 19, 1191–1239.

Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of financial economics 99, 427–446.

Bali, T.G., Engle, R.F., Murray, S., 2016. Empirical asset pricing: The cross section of stock returns. John Wiley & Sons.

Ball, R., Gerakos, J., Linnainmaa, J.T., Nikolaev, V., 2016. Accruals, cash flows, and operating profitability in the cross section of stock returns. Journal of Financial Economics 121, 28–45.

Banz, R.W., 1981. The relationship between return and market value of common stocks. Journal of financial economics 9, 3–18.

Barbee Jr, W.C., Mukherji, S., Raines, G.A., 1996. Do sales–price and debt–equity explain stock returns better than book–market and firm size? Financial Analysts Journal 52, 56–60.

Barr Rosenberg, K.R., Lanstein, R., 1998. Persuasive evidence of. Streetwise: The Best of the Journal of Portfolio Management , 48.

Basu, S., 1983. The relationship between earnings' yield, market value and return for nyse common stocks: Further evidence. Journal of financial economics 12, 129–156.

Belo, F., Lin, X., 2012. The inventory growth spread. The Review of Financial Studies 25, 278–313.

Belo, F., Lin, X., Bazdresch, S., 2014a. Labor hiring, investment, and stock return predictability in the cross section. Journal of Political Economy 122, 129–177.

Belo, F., Lin, X., Vitorino, M.A., 2014b. Brand capital and firm value. Review of Economic Dynamics 17, 150–169.

Bhandari, L.C., 1988. Debt/equity ratio and expected common stock returns: Empirical evidence. The journal of finance 43, 507–528.

Blitz, D., Huij, J., Martens, M., 2011. Residual momentum. Journal of Empirical Finance 18, 506–521.

Boudoukh, J., Michaely, R., Richardson, M., Roberts, M.R., 2007. On the importance of measuring payout yield: Implications for empirical asset pricing. The Journal of Finance 62, 877–915.

Brennan, M.J., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of financial Economics 49, 345–373.

Chan, L.K., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. Journal of Finance 51, 1681–1713.

Chan, L.K., Lakonishok, J., Sougiannis, T., 2001. The stock market valuation of research and development expenditures. The Journal of finance 56, 2431–2456.

Chordia, T., Subrahmanyam, A., Anshuman, V.R., 2001. Trading activity and expected stock returns. Journal of financial Economics 59, 3–32.

Clifford, A., Frazzini, A., 2013. The devil in hml's detail. The Journal of Portfolio Management 39, 49–68.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of financial economics 104, 383–400.

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

Daniel, K., Titman, S., 2006. Market reactions to tangible and intangible information. The Journal of Finance 61, 1605–1643.

Datar, V.T., Naik, N.Y., Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. Journal of financial markets 1, 203–219.

De Bondt, W.F., Thaler, R., 1985. Does the stock market overreact? The Journal of finance 40, 793–805.

Desai, H., Rajgopal, S., Venkatachalam, M., 2004. Value-glamour and accruals mispricing: One anomaly or two? The Accounting Review 79, 355–385.

Dichev, I.D., 1998. Is the risk of bankruptcy a systematic risk? the Journal of Finance 53, 1131–1147.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of financial economics 7, 197–226.

Eisfeldt, A.L., Papanikolaou, D., 2013. Organization capital and the cross-section of expected returns. The Journal of Finance 68, 1365–1406.

Fairfield, P.M., Whisenant, J.S., Yohn, T.L., 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. The accounting review 78, 353–371.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. the Journal of Finance 47, 427–465.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of financial economics 116, 1–22.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of political economy 81, 607–636.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. Accounting Review , 574–603.

Francis, J., LaFond, R., Olsson, P.M., Schipper, K., 2004. Costs of equity and earnings attributes. The accounting review 79, 967–1010.

Franzoni, F., Marin, J.M., 2006. Pension plan funding and stock market efficiency. the Journal of Finance 61, 921–956.

Hafzalla, N., Lundholm, R., Matthew Van Winkle, E., 2011. Percent accruals. The Accounting Review 86, 209–236.

Hahn, J., Lee, H., 2009. Financial constraints, debt capacity, and the cross-section of stock returns. The Journal of Finance 64, 891–921.

Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. The Journal of finance 55, 1263–1295.

Haugen, R.A., Baker, N.L., 1996. Commonality in the determinants of expected stock returns. Journal of financial economics 41, 401–439.

Heston, S.L., Sadka, R., 2008. Seasonality in the cross-section of stock returns. Journal of Financial Economics 87, 418–445.

Hirshleifer, D., Hou, K., Teoh, S.H., Zhang, Y., 2004. Do investors overvalue firms with bloated balance sheets? Journal of accounting and economics 38, 297–331.

Hou, K., Xue, C., Zhang, L., 2020. Replicating anomalies. Review of Financial Studies 33, 2019–2133.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of finance 45, 881–898.

Jegadeesh, N., Livnat, J., 2006. Revenue surprises and stock returns. Journal of Accounting and Economics 41, 147–171.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance 48, 65–91.

Kelly, B., Jiang, H., 2014. Tail risk and asset prices. The Review of Financial Studies 27, 2841–2871.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. The journal of finance 49, 1541–1578.

Lamont, O., Polk, C., Saaá-Requejo, J., 2001. Financial constraints and stock returns. The review of financial studies 14, 529–554.

Lev, B., Nissim, D., 2004. Taxable income, future earnings, and equity values. The accounting review 79, 1039–1074.

Li, D., 2011. Financial constraints, r&d investment, and stock returns. The Review of Financial Studies 24, 2974–3007.

Lou, D., 2014. Attracting investor attention through advertising. The Review of Financial Studies 27, 1797–1829.

Loughran, T., Wellman, J.W., 2011. New evidence on the relation between the enterprise multiple and average stock returns. Journal of Financial and Quantitative Analysis 46, 1629–1650.

Lyandres, E., Sun, L., Zhang, L., 2008. The new issues puzzle: Testing the investment-based explanation. The review of financial studies 21, 2825–2855.

Miller, M.H., Scholes, M.S., 1982. Dividends and taxes: Some empirical evidence. Journal of Political Economy 90, 1118–1141.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2011. Operating leverage. Review of Finance 15, 103–134.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of financial economics 108, 1–28.

Ortiz-Molina, H., Phillips, G.M., 2014. Real asset illiquidity and the cost of capital. Journal of Financial and Quantitative Analysis 49, 1–32.

Pástor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political economy 111, 642–685.

Penman, S.H., Richardson, S.A., Tuna, I., 2007. The book-to-price effect in stock returns: accounting for leverage. Journal of accounting research 45, 427–467.

Rajgopal, S., Shevlin, T., Venkatachalam, M., 2003. Does the stock market fully appreciate the implications of leading indicators for future earnings? evidence from order backlog. Review of Accounting Studies 8, 461–492.

Richardson, S.A., Sloan, R.G., Soliman, M.T., Tuna, I., 2005. Accrual reliability, earnings persistence and stock prices. Journal of accounting and economics 39, 437–485.

Sloan, R.G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Accounting review , 289–315.

Soliman, M.T., 2008. The use of dupont analysis by market participants. The accounting review 83, 823–853.

Thomas, J., Zhang, F.X., 2011. Tax expense momentum. Journal of Accounting Research 49, 791–821.

Thomas, J.K., Zhang, H., 2002. Inventory changes and future returns. Review of Accounting Studies 7, 163–187.

Titman, S., Wei, K.J., Xie, F., 2004. Capital investments and stock returns. Journal of financial and Quantitative Analysis 39, 677–700.

Tuzel, S., 2010. Corporate real estate holdings and the cross-section of stock returns. The Review of Financial Studies 23, 2268–2302.

Valta, P., 2016. Strategic default, debt structure, and stock returns. Journal of Financial and Quantitative Analysis 51, 197–229.

Whited, T.M., Wu, G., 2006. Financial constraints risk. The review of financial studies 19, 531–559.

Xie, H., 2001. The mispricing of abnormal accruals. The accounting review 76, 357–373.

Xing, Y., 2008. Interpreting the value effect through the q-theory: An empirical investigation. The Review of Financial Studies 21, 1767–1795.