How Option Traders Take Sides on Return Predictability*

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Abstract

We investigate how option traders take sides on the predictability of the underlying stocks, using a wide array of cross-sectional return predictors. To infer the aggregate trading direction of option end users, we look at cross-sectional differences in the prices of option portfolios replicating the stock positions, relative to the prices of the underlying stocks themselves. We find that option traders take a profitable side on signals associated with short-selling, momentum, profitability, and volatility. In contrast, they take a non-profitable side on signals that are associated with intangibles, investment, and valuation.

Keywords: Anomalies · Options · Informed trading

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1 Introduction

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

In this paper, we examine how option traders position themselves in relation to stock return predictability arising from stock anomalies. Recent literature seeks to streamline the "factor zoo" by employing option market data to identify anomalies driven by mispricing Böll et al. (2024). Analyzing option traders' positioning with respect to these anomalies can thus reveal whether traders utilize mispricing information to exploit predictability through the options market. Given the financial leverage offered by options, traders may strategically exploit such opportunities using option contracts. Consequently, directional anomaly portfolios provide a natural framework for identifying which specific signals option traders regard with higher conviction, thereby clarifying the relative predictability of these signals.

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

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

Averaged across 268 anomaly signals, we find an average long-short portfolio conversion return of 0.30% (t-statistic of 3.54) per month. This means that in the aggregated anomaly long portfolio the option-implied synthetic stock position is more expensive than the physical stock position, relative to the anomaly short portfolio which reflects that on average option traders trade in a direction that is profitable in relation to a large bulk of anomaly signals.

However, we find pronounced heterogeneity among different groups of anomalies. For example, we find an average long-short portfolio conversion return of 0.03% (t-statistic of 7.28) for anomalies pertaining to the *momentum* category, an average long-short portfolio conversion return of 0.06% (t-statistic of 5.05) for anomalies pertaining to the *volatility* category and an average long-short portfolio conversion return of 0.06% (t-statistic of 9.82) for anomalies pertaining to the *profitability* category. For some other categories, we find negative long-short conversion returns, indicating that option traders take positions that are contrary to the profitable direction relative to these signals. For example, the category *investment* exhibits an average negative long-short portfolio conversion return of -0.01% (t-statistic of -4.39). Similarly, the category *value* also exhibits a negative long-short portfolio conversion return of -0.04% (t-statistic of -8.19).

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

In addition to conversion returns, we also look at semivariance premia as alternative option price measures. We calculate upside and downside variance premia for anomaly portfolios and find largely consistent results to our analysis using conversion returns. Anomalies pertaining to the categories of *momentum* exhibit an average long-short portfolio upside variance premium of 0.05% (t-statistic of 9.61) and an average long-short portfolio downside variance premium of -0.01% (t-statistic of -7.46). This means that call options in the momentum long portfolio are relatively more expensive than call options in the momentum short portfolio and vice versa for put options, again indicating that option traders take exposure to stocks related to momentum anomalies in a profitable direction. Similarly, the *profitability* category exhibits an average long-short portfolio upside variance premium of 0.05% (t-statistic of 7.82) and an average long-short portfolio downside variance premium of -0.19% (t-statistic of -10.17). For the *volatility* category we find an average long-short portfolio upside variance premium of 0.20% (t-statistic of 12.81) and an average long-short portfolio downside variance premium of -0.40% (t-statistic of -12.17). Consistent to the results we obtain when we use conversion returns as price measure, we find an average long-short portfolio upside variance premium of -0.001% (t-statistic of -0.06) and an average long-short portfolio downside variance premium of 0.16% (t-statistic of 5.73) for anomalies pertaining to the *liquidity* category. For anomalies of the *value* category, we find mixed results. We find an average long-short portfolio upside variance premium of 0.01% (t-statistic of 1.56) and an average long-short portfolio downside variance premium of 0.08% (t-statistic of 6.95), indicating that call and put options are relatively more expensive in the anomaly long portfolio compared to the anomaly short portfolio.

We are also interested in which time periods option traders on average demand options of stocks related to anomaly signals. To this extent, we average long-short portfolio conversion returns across all 153 anomaly signals which we use in our study and relate the aggregate long-short conversion return to various measures of arbitrage frictions such as intermediary capital constraints, the TED spread, shorting fees and bid-ask spreads of stocks and options. Other studies have already established a connection between the gap between synthetic and physical stock prices and frictions: Hiraki and Skiadopoulos (2021) assume the gap as a measure of the impact of frictions on asset prices without empirically demonstrating this relationship. Muravyev et al. (2023) utilize a related measure, namely the difference between at-the-money call and put implied volatilities, as a gauge for options-implied stock borrowing fees. Our findings suggest that intermediary capital constraints significantly affect the aggregate long-short conversion return, highlighting the important role of financial intermediaries as arbitrageurs.

Related literature Our study makes several contributions to the literature. First, Han et al. (2024) investigates customer option traders' positioning in response to short-term reversal signals. Hollstein and Wese Simen (2024) explores the trading behaviors of option traders across 22 anomalies, classified into three broad categories: options and volatility, liquidity, and accounting and equity trading. While their focus is primarily on option-specific anomalies, with limited attention to stock anomalies, our research takes a different approach. We focus on stock market anomalies, substantially expanding our analysis to include 268 anomalies across 10 categories. Of these, 153 serve as primary predictors for our main analysis, while the remaining 115 function as placebo variables for robustness testing.

Second, recent literature has increasingly focused on identifying which anomalies stem from mispricing. Böll et al. (2024) leverages option volume information to develop the Anomaly Concentration Spread (ACS) measure, which categorizes anomalies as either mispricing-driven or consensual. Their findings indicate that momentum and profitability anomalies primarily result from mispricing. Further, van Binsbergen et al. (2023) demonstrates that momentum and profitability factors can amplify mispricing in equity markets. Our research extends these findings by showing that option traders construct directional positions specifically designed to correct momentum and profitability mispricing in options markets. In contrast, for value and investment anomalies, option traders' positions merely track the direction of mispricing.

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

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

2 Data

We use daily security price and options data from the OptionMetrics Ivy DB database. Our analysis is conducted on a cross-section of common stocks, actively traded at NYSE, AMEX, or Nasdaq. Naturally, our sample is limited to stocks with actively traded options, which leads to the fact that our cross-section consists of rather liquid stocks with large market capitalization. Böll et al. (2023) show that stock anomalies are on average weaker but still significant on optionable stocks than on stocks without options. They also show that the difference in the average effect size can be explained entirely by differences in the size and liquidity of the stocks in the two samples. With respect to the time-series span, our main sample covers the period from January 1996 to June 2021.

We obtain anomaly signals from Chen and Zimmermann (2021) and consider two different set of anomalies. On the one hand, we study all anomalies featured in their data base. On the other hand, we drop all anomalies that they categorize as "placebos" and only consider those they call "predictors". "Placebos" include characteristics that were typically studied by the authors of the original papers for the purpose of benchmarking and did not turn out to have a significant cross-sectional correlation with future returns. To ensure consistency and robustness, we restrict our attention to continuous signals that are not derived from options data (option-based anomaly signals are discussed by Hollstein and Wese Simen, 2024) and that provide sufficient data coverage to compute long-short returns. After applying these filters, we retain 268 signals in the full anomaly set and 153 "predictors," which we further group into 10 categories using a clustering approach (see Appendix A for details). Table 4 provides an overview of the 268 anomaly signals used in our analysis.

2.1 Conversion returns

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

In detail, the return decomposition reads as

$$\begin{aligned} r_S^e &= \frac{S_T - S_0}{S_0} - r_{0,T} \\ &= \frac{F_T - F_0 + (S_T - F_T) - (S_0 - F_0)}{S_0} - r_{0,T} \\ &= \frac{F_T - F_0}{S_0} + \left(\frac{G_T - G_0}{S_0} - r_{0,T} \right) \\ &= r_F + r_G^e, \end{aligned} \tag{1}$$

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

For the interpretation of Equation (1), it is instrumental to follow Ofek et al. (2004) and define the *synthetic stock price* as

$$S_t^* := C_t - P_t + \frac{X}{1 + r_{t,T}}. \tag{2}$$

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

For the special case of at-the-money-forward options, i.e., with $X = S_0(1 + r_{0,T})$, substituting Equation (2) in Equation (1) shows that the returns on the synthetic forward and the conversion have handy interpretations:

$$\begin{aligned} r_F &= \frac{S_T^* - S_0^*}{S_0} - r_{0,T} \\ r_G^e &= \frac{S_0^* - S_0}{S_0} \end{aligned} \tag{3}$$

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

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

Then, for each day and stock in our sample, we select a pair of call and put options expiring at the upcoming standard maturity date. We follow Jacobs et al. (2024) and switch to the standard maturity after the next maturity (i.e. to the next month), if time to maturity is shorter than 15 days. This procedure avoids using prices of options with very short maturities, which can be driven by short-term speculation and traders rolling over maturing positions to options with longer maturities or weeklys. As a consequence, all options in our sample have times-to-maturity between 15 and 49 days.

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

Conversion prices are calculated from mid prices between bid and ask of all asset involved. We are aware of the fact that actual investors cannot trade at the mid. The goal of our analysis is not to demonstrate that there are arbitrage opportunities in the options market. Indeed, we show in Section 3.4 that transaction costs exceed conversion returns by a large margin. Still, conversion returns tell us if option mid prices move away from their frictionless counterparts, indicating heightened demand for that option.

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

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

Summary statistics. Panel A of Table 1 shows summary statistics of of our sample of (excess) conversion returns, pooled across assets and time. The sample consists of around 9 million observations, corresponding to a cross-section of around 1370 stocks per day. The average excess conversion return is -12 basis points. This could hint at two channels. First, the interest rate used to calculate excess returns could be higher on average than the interest rate implied by the options used in our sample. Second, high average demand or low market maker supply for put options, relative to call options, could, on average, pull excess conversions to the negative domain. Since our later analysis will focus on spreads in conversions across different anomaly portfolios, the level of excess conversion returns is of secondary interest to our analysis.

More interestingly, there is pronounced variation in conversion returns with a pooled standard deviation of around 0.5 percent. Our analysis in Section 3 shows that this variation is cross-sectionally correlated with many anomaly signals, hinting at pronounced option demand for specific underlyings.

2.2 Semivariance premia

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

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

$$SV_t^{\mathbb{Q}-} = \int_0^{S_t(1+r_{t,T})} \frac{2(1+\log(S_t(1+r_{t,T})/X))}{X^2} P_t(T-t,X)dX \tag{4}$$

$$SV_t^{\mathbb{Q}+} = \int_{S_t(1+r_{t,T})}^{\infty} \frac{2(1-\log(X/S_t(1+r_{t,T})))}{X^2} C_t(T-t,X)dX. \tag{5}$$

Here, we augmented our notation of C and P from Section 2.1 to make explicit that the options have strike prices X and time-to-maturities $T-t$. For the ease of notation, we omit the stock index i from all operators, with the implicit understanding that all computations will be performed for each stock individually.

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

Consistent with the conversions, estimated as explained in Section 2.1, we select a time-to-maturity of 30 days. Since the surface file often reports negative implied volatilities, we drop stock-days with less than four distinct positive call or put implied volatilities. We approximate the integrals in Equations (4) and (5) by calculating out-of-the-money call and put prices corresponding to 1000 moneyness levels each. For that purpose, we apply a cubic smoothing spline across moneyness values ranging from 0.3% to 300%. Here, moneyness is defined as the ratio of the strike price to the ex-dividend stock price, the latter being calculated as the difference between the time t stock price and all dividend payments between t and T.

Following Jiang and Tian (2005), to address potential interpolation and extrapolation issues, we set the implied volatilities for moneyness levels beyond the observed range in the OptionMetrics data to the corresponding implied volatilities at the boundary moneyness values. We then calculate option prices, by substituting the interpolated implied volatilities, together with the other relevant option characteristics into the Black and Scholes (1973) formula. Finally, we implement the trapezoidal rule to numerically compute the risk-neutral semivariances in Equation 4 and Equation 5.

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

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

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

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

$$RV^+_{\tau_1,\tau_2} = \sum_{\tau=\tau_1}^{\tau_2} r_\tau^2 \mathbb{1}_{r_\tau>0} \quad \text{and} \quad RV^-_{\tau_1,\tau_2} = \sum_{\tau=\tau_1}^{\tau_2} r_\tau^2 \mathbb{1}_{r_\tau<0} \tag{8}$$

We calculate expectations for the next 22 trading days, which is equivalent to the 30 days-to-maturity convention of OptionMetrics. We run regressions 6 and 7 separately for each stock using the full sample period. We use the estimated coefficients to estimate the semi-variances for each stock on each day t and $* \in \{-,+\}$ as

$$\begin{aligned} SV_t^{\mathbb{P}*} = a^+ &+ b_1^* SV_t^{\mathbb{Q}-} + b_2^* SV_t^{\mathbb{Q}+} + b_3^* RV^-_{t-21,t} + b_4^* RV^+_{t-21,t} \\ &+ b_5^* RV^-_{t-4,t} + b_6^* RV^+_{t-4,t} + b_7^* RV_t^- + b_8^+ RV^+_{t,t}. \end{aligned} \tag{9}$$

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

$$SVP_t^- = SV_t^{\mathbb{Q}-} - SV_t^{\mathbb{P}-} \quad \text{and} \quad SVP_t^+ = SV_t^{\mathbb{Q}+} - SV_t^{\mathbb{P}+} \tag{10}$$

By construction, the semi-variance risk premia add up to the total variance risk premia. This is true since the physical semivariance estimates employ the same predictive variables in both of the equations (6) and (7). In our later analysis, $SVP^-_{i,t}$ is interpreted as a measure for the expensiveness of put options and $SVP^+_{i,t}$ is our measure for the expensiveness of call options for stock i on day t.

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

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

3 Anomaly portfolios in stock and options markets

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

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

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

3.1 The average anomaly

To get an initial impression and before we discuss individual anomalies, we consider the average anomaly. To do this, we compute equally weighted averages of the portfolio returns for all anomaly-long portfolios and all anomaly-short portfolios, and examine the differences. Table 2 shows the results in Panel A when we average over all 268 signals in our sample.

We find a difference in the conversion returns between the average anomaly-long and the anomaly-short portfolio of around one basis point per month. Although this value is very small, it is very precisely estimated, with a t-statistic of 9.04. This high precision is due to the fact that conversion returns are price differences, not highly volatile returns that are subject to uncertainty over the holding period. Additionally, we average over 268 time series and over 6,600 time points.

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

Panel B shows the same statistics, but we now average across those 153 anomalies that are labeled as "predictors" by Chen and Zimmermann (2021). If options investors only trade against profitable anomalies, we should exclude "placebos" from the analysis. The average return difference on stocks in predictor-sorted decile portfolios is rather similar to the the average return difference associated to all signals. This points to the fact that the optionable sample between 1996 and 2021 is different from the original samples the predictors and placebos have been tested in. The conversion spread is again positive and larger than in Panel A. The semivariance premia are consistent with this finding. The spread in upper semivariance premia is larger and the spread in lower semivariance premia is lower on the set of predictors than on the full set of anomaly signals.

Some of the predictors on the full sample could turn out uninformative on the set of optionable stocks. As discussed by Böll et al. (2023), optionable stocks are rather liquid and have large market capitalization on average. It is well-known that some anomalies do not yield significant returns on such stocks. For Panel C, we only average across anomaly signals with significantly positive average returns on the set of optionable stocks between 1996 and 2021. Several anomaly signals happen to yield even significantly negative returns on our sample, although we sign all anomaly signals according to the sign suggested in the original papers.

The spread in average stock returns is, by construction, higher for significant signals than on the other two sets of signals. However, we also see a massive increase in the conversion spread. The difference between conversion returns in the high and low anomaly portfolios amounts to around 7 basis points. In other words, when looking exclusively at anomalies that are strong on the sample of stocks used in our analysis, we find that anomalies are larger on the stock market than on the options market and the difference amounts to almost 7 basis points per month. As the average effect size for these anomalies is 0.78% per month, this means that the average returns on the replicating portfolios amounts to only 0.72% per months. This gap is also economically significant. The massive semivariance premia, especially on the downside, indicate that investors use calls and puts, but primarily the latter, to trade against anomalies in the options market.

3.2 Individual anomalies

Table 5 shows stock, forward and conversion return differences between the long and the short decile portfolio corresponding to all 268 individual anomaly signals in our sample. Likewise, Table 6 shows long-short differences in upper and lower semivariance premia. We find strong variation in conversion excess returns and semivariance premia across different kinds of anomalies. We discuss a few prominent examples here.

The momentum anomaly *Mom12m* exhibits a long-short conversion return difference of 0.12% (t-statistic of 7.36). This indicates that on average there is demand for trading against stocks in the momentum short portfolio using options, e.g. by buying puts or selling calls. An alternative explanation of the positive long-short conversion return could be that option traders buy calls or sell puts in the momentum long portfolio. In any case, the positive long-short portfolio conversion return for the momentum anomaly indicates that on average option traders trade in a direction that is profitable to them in relation to this anomaly signal.

Again starting with the momentum anomaly *Mom12m*, we find a long-short portfolio downside variance premium of -0.16% (t-statistic of -6.13). This means that put options in the momentum short portfolio are relatively more expensive than in the anomaly long portfolio. Looking at the upside variance premium, we find a long-short portfolio upside variance premium of 0.02% (t-statistic of 1.12). This suggests that call options in the momentum long portfolio are more expensive compared to those in the momentum short portfolio, though this price differential lacks statistical significance. These results indicate that option traders use calls and puts to trade against the momentum anomaly.

Another anomaly where we find positive and significant long-short conversion returns is the profitability anomaly *CBOperProf*. The anomaly's long-short conversion return is 0.15% (t-statistic of 9.10). This again indicates that on average option traders use options to get exposure to stocks related to this anomaly in a direction that is profitable to them.

The long-short portfolio downside variance premium is -0.41% (t-statistic of -19.47). Similar to before, this implies that puts in the profitability anomaly's short portfolio are relatively more expensive than in the anomaly's long portfolio. For the upside variance premium we find a positive long-short portfolio upside variance premium of 0.08% (t-statistic of 7.70), meaning that calls are relatively expensive in the long portfolio of this anomaly. Following demand-based option pricing theory, this indicates that option traders demand call and put options in directions that are profitable to them relative to this anomaly signal.

However, there is heterogeneity among anomalies. For example, the quarterly book-to-market ratio *BMq*, a classic value anomaly, exhibits a negative long-short conversion return of -0.05% (t-statistic of -4.58). At first sight, this finding suggests that for this anomaly, option traders take exposure to stocks related to this anomaly in a direction that is not profitable to them. However, one has to take into account that this anomaly signal is negatively related to future returns on the sample of optionable stocks between 1996 and 2021. It is well-known that many value-anomalies have performed poorly, especially since 2000, which could have also affected the trading behavior of option market participants.

BMq is not a special case. Out of 268 signals, 72 have significantly negative long-short conversion return spreads. Of these, 35 have negative long-short stock return differences on our sample, and another 29 have insignificantly positive stock return differences.

3.3 Anomaly categories

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

The *profitability* category exhibits the highest average long-short conversion return of 0.06% (t-statistic = 9.82), primarily driven by the anomaly *CBOperProf*, a cash-based operating profitability measure introduced by Ball et al. (2016). The category with the second-highest average long-short excess conversion return is *volatility*, largely due to the anomaly *IdioVolAHT*, which delivers individual effect with a return of 0.20% (t-statistic = 6.53). Within the *issuance* category, the anomaly *ShortInterest* generates the second-highest individual long-short excess conversion return of 0.19% (t-statistic = 1.95). This finding is consistent with a substantial body of literature linking the options market to synthetic short selling (e.g., Figlewski and Webb (1993); Danielsen and Sorescu (2001); Sorescu (2000), among others). Other categories in which option market activity aligns with anomaly-based return predictability include *momentum* and *accurals*, among others. Conversely, option trader positioning appears to be against the profitable anomaly direction in categories such as *value* and *investment*. The *value* category exhibits the most negative long-short conversion return at -0.04% (t-statistic = -8.19), followed by *investment* at -0.01% (t-statistic = -4.39).

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

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

3.4 Transaction costs

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

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

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

4 The impact of frictions

4.1 Empirical design and data

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

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

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

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

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

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

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

$$\begin{aligned} r^{ls}_{C,t} = \alpha_a + \beta_{a,icr}\, ICR_{t-1} + \beta_{a,ted}\, TED_{t-1} + \beta_{a,bas}\, Bidask^{stock}_{t-1} \\ + \beta_{a,bao}\, Bidask^{call}_{t-1} + \beta_{a,sf}\, SF_{t-1} + \beta_{a,lag}\, r^{ls}_{C,t-1} + \epsilon_{a,t}, \end{aligned} \tag{11}$$

where $r^{ls}_{C,t}$ is the conversion long-short return of the average anomaly in month t. Since all friction measures are realized at the end of the month prior to the initiation of the conversion positions Equation (11) is a predictive regression.

4.2 Empirical findings

Table 3 presents the regression results. Columns (1) to (5) report estimates from univariate regressions, while column (6) provides results from a multivariate regression incorporating all friction measures. In the univariate specifications, the intermediary capital ratio is negatively and significantly related to conversion returns, with a coefficient of -0.41 and a t-statistic of -3.73. Similarly, the TED spread exhibits a positive and statistically significant association with conversion returns, with a coefficient of 0.34 and a corresponding t-statistic of 2.19. These findings suggest that conversion returns tend to be higher in periods of elevated intermediary capital constraints (corresponding to a low ICR) and elevated funding constraints (corresponding to a high TED spread). In the univariate specifications, we also find a negative coefficient of the option bid-ask spread. This finding indicates that conversion spreads are on average lower if options are more liquid, hinting at the fact that option market participants trade more actively against anomalies when the trading costs in the options market are low.

However, in the multivariate regression, only the intermediary capital ratio remains statistically significant, with a coefficient of -0.23 and a t-statistic of -3.64. These results highlight the role of financial intermediaries as key arbitrageurs in the options market, particularly when arbitrage capital is abundant. Interestingly, short-selling constraints do not turn out to be significantly related to conversion spreads in the time series.

4.3 Discussion

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

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

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

5 Conclusion

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

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

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

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

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

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

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

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

Figures

Figure 1: Long-short conversion returns across economic categories
In each month, we aggregate equally-weighted long-short conversion returns of anomalies across each economic category. We plot the average long-short conversion return of each economic category on the y-axis and the name of the economic category on the x-axis. The error bars in red represent a 95% confidence interval for the average long-short conversion returns. Standard errors are adjusted according to Newey and West (1987). We consider 153 predictor anomaly signals which are grouped into 10 categories. The sample covers the period from January 1996 to June 2021.

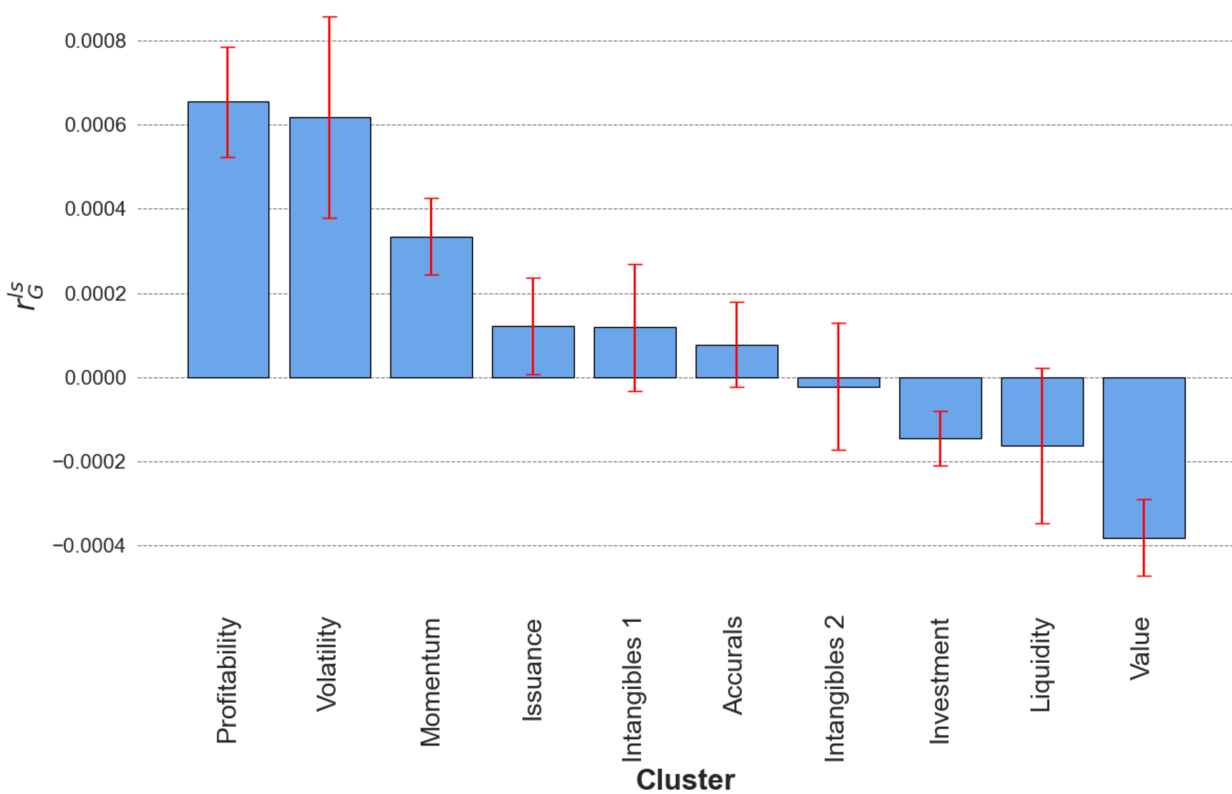


Figure 2: Long-short conversion returns and trading costs across economic categories In each month, we aggregate equally-weighted long-short conversion returns of anomalies across each economic category. We plot the average long-short conversion return of each economic category on the y-axis and the name of the economic category on the x-axis. The bars in red represent the trading costs centered around the mean long-short conversion return for the respective strategy. We multiply option quoted half spreads from OptionMetrics with a multiplier derived from Muravyev and Pearson (2020) to calculate effective half spreads. The cost categories $Costs_{ES}$, $Costs_{ADJES}$, $Costs_{ALGOES}$ show costs when we use multipliers based on the different kinds of spreads that Muravyev and Pearson (2020) provide. We consider 153 predictor anomaly signals which are grouped into 10 categories. The sample covers the period from January 1996 to June 2021.

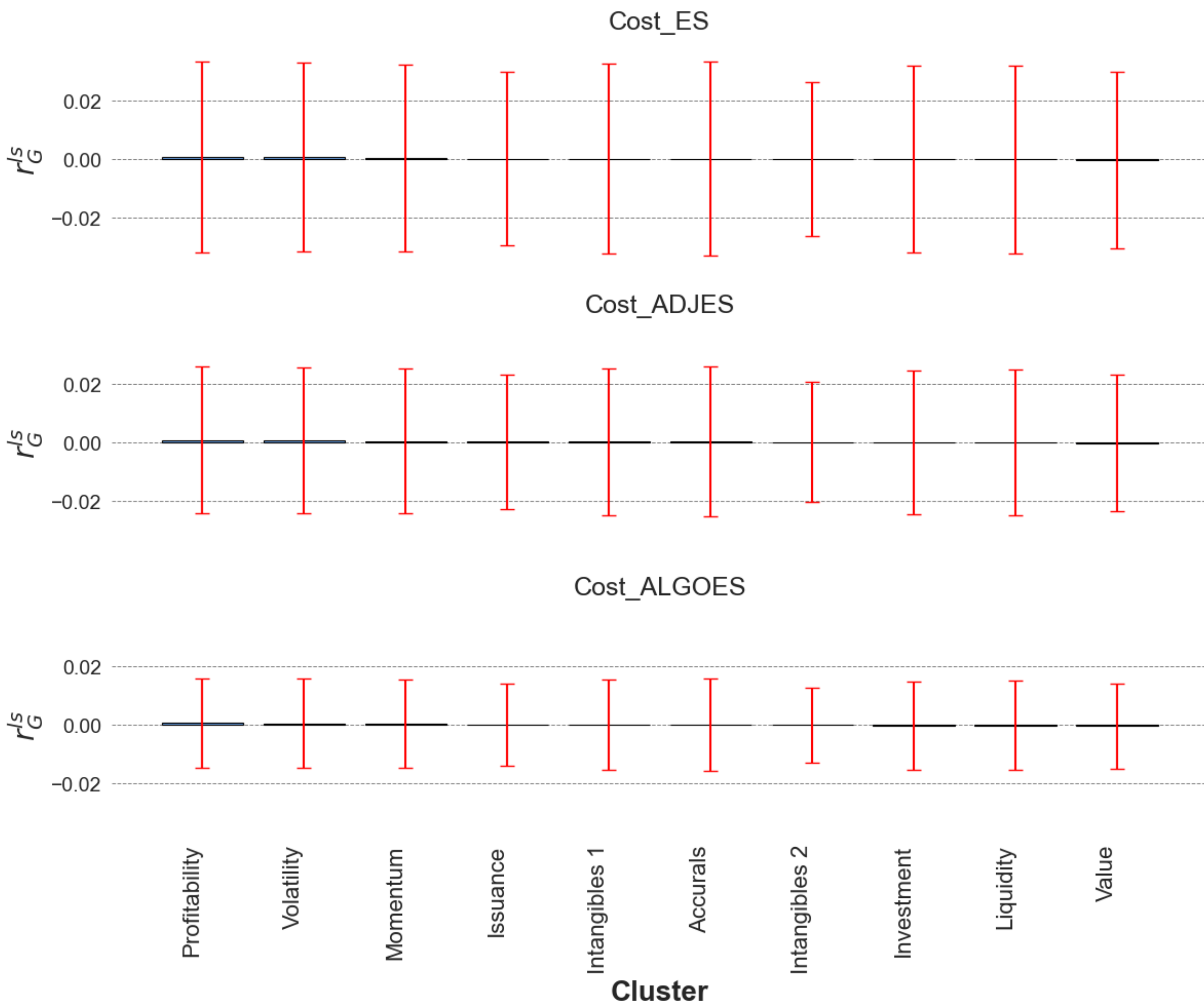
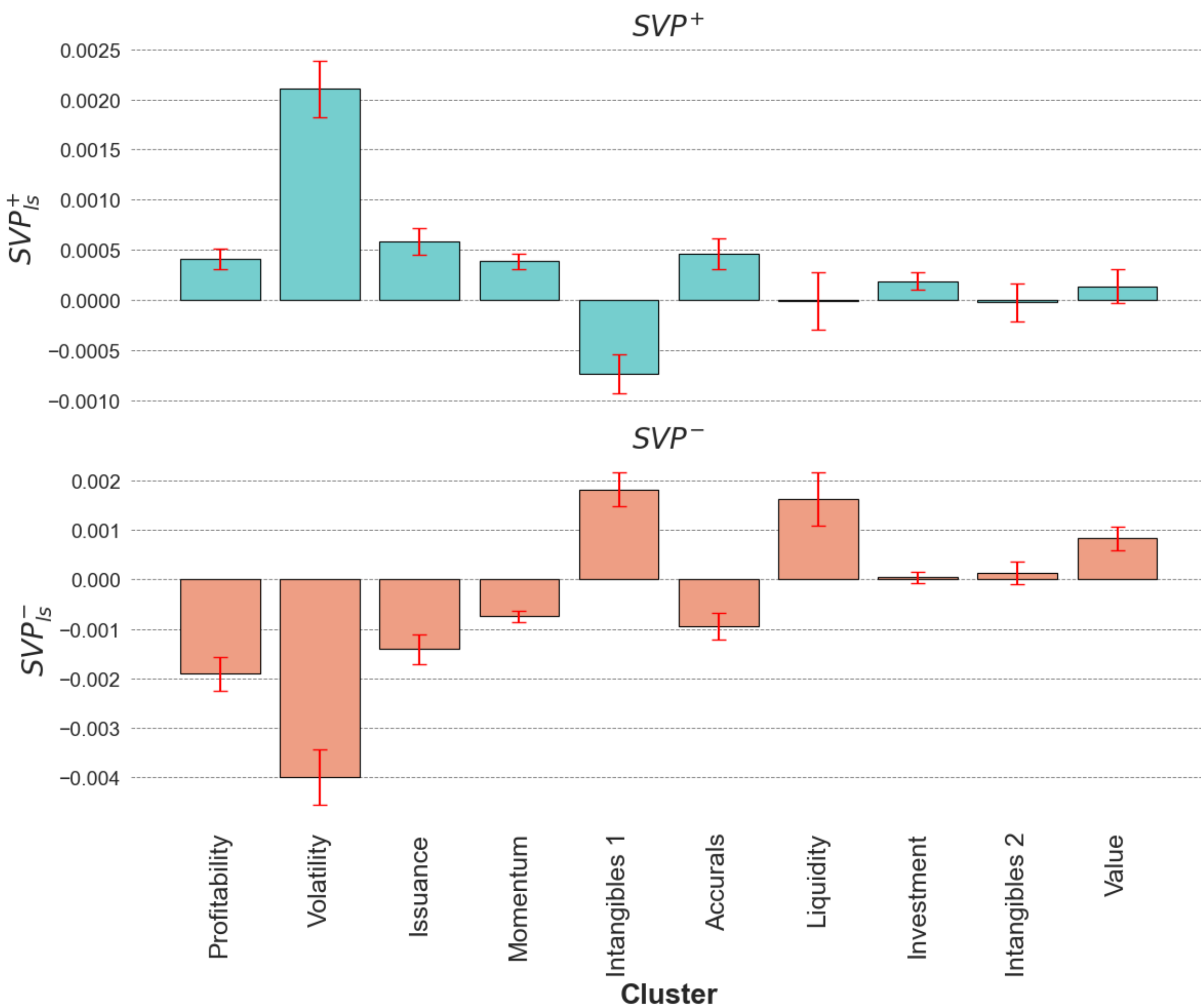


Figure 3: Semivariance premia across economic categories
In each month, we aggregate equally-weighted long-short semivariance premia of anomalies across each economic category. We plot the average long-short semivariance premia of each economic category on the y-axis and the name of the economic category on the x-axis. The error bars in red represent a 95% confidence interval for the average long-short conversion returns. Standard errors are adjusted according to Newey and West (1987). We consider 153 predictor anomaly signals which are grouped into 10 categories. Because we use security price data from OptionMetrics to compute semivariance premia, the sample covers the period from February 1996 to June 2021.



Tables

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

	N	mean	std	25%	50%	75%	skewness	kurtosis
Panel A: Conversion returns								
r_G	9,075,240	0.04	0.54	-0.15	0.07	0.29	-0.54	3.76
r_G^e	9,075,240	-0.12	0.52	-0.29	-0.06	0.09	-0.67	4.42
Panel B: Semivariance premia								
SVP^+	14,505,391	-0.14	0.30	-0.26	-0.06	0.04	-1.31	1.72
SVP^-	14,505,391	0.40	0.53	0.02	0.24	0.65	1.22	0.88
VP	14,505,391	0.22	0.58	-0.14	0.10	0.51	0.79	0.46

Table 2: Long-short conversion returns and semivariance premia averaged across all anomaly signals

In each month, we average equally-weighted long-short conversion returns and semivariance premia across all 153 predictors that we consider in our study. t-statistics are shown in parantheses. Standard errors are adjusted according to Newey and West (1987). Excess conversion returns and semivariance premia are displayed in percentages. The sample covers the period from January 1996 to June 2021 for long-short conversion returns and February 1996 to June 2021 for long-short semivariance premia.

	Portfolio 1	Portfolio 10	10-1	t(10-1)
Panel A: All 268 anomalies				
r_S	0.1050	0.4082	0.3032	(3.54)
r_G^e	-0.1753	-0.1610	0.0143	(9.04)
SVP^+	-0.2228	-0.2104	0.0124	(8.17)
SVP^-	0.5305	0.5123	-0.0183	(-4.72)
Panel B: 153 predictors				
r_S	0.2864	0.5690	0.2827	(3.25)
r_G^e	-0.1813	-0.1609	0.0205	(8.13)
SVP^+	-0.2380	-0.2010	0.0370	(6.18)
SVP^-	0.5428	0.4800	-0.0628	(-2.38)
Panel C: 66 significant signals on optionable sample				
r_S	-0.2064	0.5774	0.7838	(4.85)
r_G^e	-0.2105	-0.1430	0.0675	(5.42)
SVP^+	-0.2509	-0.1951	0.0558	(10.09)
SVP^-	0.6360	0.4434	-0.1926	(-11.61)

Table 3: Long-short conversion return predictability
In each month, we average equally-weighted long-short conversion returns of all 153 anomalies that we consider in our study. We show the results for monthly predictive regressions of the aggregated long-short conversion return on a set of predictors indicated by the rows. Columns (1) to (5) contain the results for univariate regressions, while column (6) contains the results for a multivariate regression including all the predictors. We standardize the independent variables and multiply the dependent variable by 1000 for the sake or readability. Each row before last row reports the estimated coefficient and t-statistics are shown in parentheses. Standard errors are adjusted according to Newey and West (1987).The last row depicts the adjusted R^2. *, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively. Because shorting fee data is only available from July 2006, the sample ranges from August 2006 to June 2021.

	Dependent variable: Average (all anomalies) long-short $r_{G,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.09***	1.09***	1.09***	1.09***	1.09***	1.09***
	(8.69)	(19.38)	(18.88)	(18.02)	(18.29)	(20.93)
SF_{t-1}	0.13					0.03
	(1.43)					(0.43)
ICR_{t-1}		-0.41***				-0.23***
		(-3.73)				(-3.64)
TED_{t-1}			0.34**			0.12
			(2.19)			(1.70)
$Bidask^{stock}_{t-1}$				0.04		-0.19*
				(0.31)		(-1.79)
$Bidask^{call}_{t-1}$					-0.18**	0.02
					(-2.39)	(0.25)
$retG_{t-1}$						0.54***
						(6.92)
$Adj.R^2$	0.01	0.13	0.06	0.01	0.03	0.31

Table 4: Overview over anomaly signals

This table describes the 268 anomaly signals from Chen and Zimmermann (2021) that we use in our analyses. We limit ourselves to continuous signals which are not constructed using options data and which have enough data coverage to calculate long-short returns. This leaves us with 153 predictors that we consider in our study and 115 placebos. we further cluster them into 10 groups based on our clustering method.

Acronym	Description	Category	Author
		Accruals	
AOP	Analyst Optimism	Predictor	Frankel and Lee (1998)
AbnormalAccruals	Abnormal Accruals	Predictor	Xie (2001)
AbnormalAccrualsPercent	Percent Abnormal Accruals	Placebo	Hafzalla, Lundholm, Van Winkle (2011)
Accruals	Accruals	Predictor	Sloan (1996)
BPEBM	Leverage component of BM	Predictor	Penman, Richardson and Tuna (2007)
CF	Cash flow to market	Predictor	Lakonishok, Shleifer, Vishny (1994)
CFq	Cash flow to market quarterly	Placebo	Lakonishok, Shleifer, Vishny (1994)
ChNWC	Change in Net Working Capital	Predictor	Soliman (2008)
EP	Earnings-to-Price Ratio	Predictor	Basu (1977)
EPq	Earnings-to-Price Ratio	Placebo	Basu (1977)
EntMult	Enterprise Multiple	Predictor	Loughran and Wellman (2011)
EntMult_q	Enterprise Multiple quarterly	Placebo	Loughran and Wellman (2011)
EquityDuration	Equity Duration	Predictor	Dechow, Sloan and Soliman (2004)
ExclExp	Excluded Expenses	Predictor	Doyle, Lundholm and Soliman (2003)
IntrinsicValue	Intrinsic or historical value	Placebo	Frankel and Lee (1998)
KZ	Kaplan Zingales index	Placebo	Lamont, Polk and Saa-Requejo (2001)
KZ_q	Kaplan Zingales index quarterly	Placebo	Lamont, Polk and Saa-Requejo (2001)
OperProf	operating profits / book equity	Predictor	Fama and French (2006)
OperProfLag	operating profits / book equity	Placebo	Fama and French (2006)
OperProfLag_q	operating profits / book equity	Placebo	Fama and French (2006)
PctAcc	Percent Operating Accruals	Predictor	Hafzalla, Lundholm, Van Winkle (2011)
RoE	net income / book equity	Predictor	Haugen and Baker (1996)
SP	Sales-to-price	Predictor	Barbee, Mukherji and Raines (1996)
SP_q	Sales-to-price quarterly	Placebo	Barbee, Mukherji and Raines (1996)
cfp	Operating Cash flows to price	Predictor	Desai, Rajgopal, Venkatachalam (2004)
currat	Current Ratio	Placebo	Ou and Penman (1989)
quick	Quick ratio	Placebo	Ou and Penman (1989)
rd_sale_q	R&D to sales	Placebo	Chan, Lakonishok and Sougiannis (2001)
salecash	Sales to cash ratio	Placebo	Ou and Penman (1989)
secured	Secured debt	Placebo	Valta (2016)
		Intangibles 1	
Activism1	Takeover vulnerability	Predictor	Cremers and Nair (2005)
AssetLiquidityBook	Asset liquidity over book assets	Placebo	Ortiz-Molina and Phillips (2014)
AssetLiquidityBookQuart	Asset liquidity over book (qtrly)	Placebo	Ortiz-Molina and Phillips (2014)
Cash	Cash to assets	Predictor	Palazzo (2012)
ChangeInRecommendation	Change in recommendation	Predictor	Jegadeesh et al. (2004)
Herf	Industry concentration (sales)	Predictor	Hou and Robinson (2006)
HerfAsset	Industry concentration (assets)	Predictor	Hou and Robinson (2006)
HerfBE	Industry concentration (equity)	Predictor	Hou and Robinson (2006)
MomOffSeason16YrPlus	Off season reversal years 16 to 20	Predictor	Heston and Sadka (2008)
NOA	Net Operating Assets	Predictor	Hirshleifer et al. (2004)
NetDebtPrice	Net debt to price	Predictor	Penman, Richardson and Tuna (2007)

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Table 4 – continued from previous page

Acronym	Description	Signal Type	Author
NetDebtPrice_q	Net debt to price	Placebo	Penman, Richardson and Tuna (2007)
RD	R&D over market cap	Predictor	Chan, Lakonishok and Sougiannis (2001)
RD_q	R&D over market cap quarterly	Placebo	Chan, Lakonishok and Sougiannis (2001)
ReturnSkew3F	Idiosyncratic skewness (3F model)	Predictor	Bali, Engle and Murray (2015)
ReturnSkewCAPM	Idiosyncratic skewness (CAPM)	Placebo	Bali, Engle and Murray (2015)
ReturnSkewQF	Idiosyncratic skewness (Q model)	Placebo	Bali, Engle and Murray (2015)
rd_sale	R&D to sales	Placebo	Chan, Lakonishok and Sougiannis (2001)
tang	Tangibility	Predictor	Hahn and Lee (2009)
tang_q	Tangibility quarterly	Placebo	Hahn and Lee (2009)
	Intangibles 2		
AdExp	Advertising Expense	Predictor	Chan, Lakonishok and Sougiannis (2001)
AssetTurnover	Asset Turnover	Placebo	Soliman (2008)
AssetTurnover_q	Asset Turnover	Placebo	Soliman (2008)
BrandCapital	Brand capital to assets	Placebo	Belo, Lin and Vitorino (2014)
CapTurnover	Capital turnover	Placebo	Haugen and Baker (1996)
CapTurnover_q	Capital turnover (quarterly)	Placebo	Haugen and Baker (1996)
ChangeRoA	Change in Return on assets	Placebo	Balakrishnan, Bartov and Faurel (2010)
DelLTI	Change in long-term investment	Predictor	Richardson et al. (2005)
DelSTI	Change in short-term investment	Placebo	Richardson et al. (2005)
DelayNonAcct	Non-accounting component of price delay	Placebo	Callen, Khan and Lu (2013)
EarnSupBig	Earnings surprise of big firms	Predictor	Hou (2007)
EarningsSurprise	Earnings Surprise	Predictor	Foster, Olsen and Shevlin (1984)
FR	Pension Funding Status	Predictor	Franzoni and Marin (2006)
FRbook	Pension Funding Status	Placebo	Franzoni and Marin (2006)
OPLeverage	Operating leverage	Predictor	Novy-Marx (2011)
OPLeverage_q	Operating leverage (qtrly)	Placebo	Novy-Marx (2011)
OrderBacklog	Order backlog	Predictor	Rajgopal, Shevlin, Venkatachalam (2003)
pchcurrat	Change in Current Ratio	Placebo	Ou and Penman (1989)
pchquick	Change in quick ratio	Placebo	Ou and Penman (1989)
salerec	Sales to receivables	Placebo	Ou and Penman (1989)
	Investment		
AssetGrowth	Asset growth	Predictor	Cooper, Gulen and Schill (2008)
AssetGrowth_q	Asset growth quarterly	Placebo	Cooper, Gulen and Schill (2008)
ChAssetTurnover	Change in Asset Turnover	Predictor	Soliman (2008)
ChEQ	Growth in book equity	Predictor	Lockwood and Prombutr (2010)
ChInv	Inventory Growth	Predictor	Thomas and Zhang (2002)
ChNCOA	Change in Noncurrent Operating Assets	Placebo	Soliman (2008)
ChNCOL	Change in Noncurrent Operating Liab	Placebo	Soliman (2008)
ChNNCOA	Change in Net Noncurrent Op Assets	Predictor	Soliman (2008)
ChPM	Change in Profit Margin	Placebo	Soliman (2008)
DelCOA	Change in current operating assets	Predictor	Richardson et al. (2005)
DelCOL	Change in current operating liabilities	Predictor	Richardson et al. (2005)
DelEqu	Change in equity to assets	Predictor	Richardson et al. (2005)
GrAdExp	Growth in advertising expenses	Predictor	Lou (2014)
GrLTNOA	Growth in long term operating assets	Predictor	Fairfield, Whisenant and Yohn (2003)
GrSaleToGrInv	Sales growth over inventory growth	Predictor	Abarbanell and Bushee (1998)
GrSaleToGrOverhead	Sales growth over overhead growth	Predictor	Abarbanell and Bushee (1998)
GrSaleToGrReceivables	Change in sales vs change in receiv	Placebo	Abarbanell and Bushee (1998)
InvGrowth	Inventory Growth	Predictor	Belo and Lin (2012)
InvestPPEInv	change in ppe and inv/assets	Predictor	Lyandres, Sun and Zhang (2008)

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Table 4 – continued from previous page

Acronym	Description	Signal Type	Author
LaborforceEfficiency	Laborforce efficiency	Placebo	Abarbanell and Bushee (1998)
OrderBacklogChg	Change in order backlog	Predictor	Baik and Ahn (2007)
PctTotAcc	Percent Total Accruals	Predictor	Hafzalla, Lundholm, Van Winkle (2011)
TotalAccruals	Total accruals	Predictor	Richardson et al. (2005)
dNoa	change in net operating assets	Predictor	Hirshleifer, Hou, Teoh, Zhang (2004)
hire	Employment growth	Predictor	Bazdresch, Belo and Lin (2014)
pchsaleinv	Change in sales to inventory	Placebo	Ou and Penman (1989)
saleinv	Sales to inventory	Placebo	Ou and Penman (1989)
sgr	Annual sales growth	Placebo	Lakonishok, Shleifer, Vishny (1994)
sgr_q	Annual sales growth quarterly	Placebo	Lakonishok, Shleifer, Vishny (1994)
	Issuance		
CompEquIss	Composite equity issuance	Predictor	Daniel and Titman (2006)
CompositeDebtIssuance	Composite debt issuance	Predictor	Lyandres, Sun and Zhang (2008)
DelFINL	Change in financial liabilities	Predictor	Richardson et al. (2005)
DelNetFin	Change in net financial assets	Predictor	Richardson et al. (2005)
FirmAge	Firm age based on CRSP	Predictor	Barry and Brown (1984)
GrGMToGrSales	Gross margin growth to sales growth	Placebo	Abarbanell and Bushee (1998)
MomOffSeason06YrPlus	Off season reversal years 6 to 10	Predictor	Heston and Sadka (2008)
MomSeason16YrPlus	Return seasonality years 16 to 20	Predictor	Heston and Sadka (2008)
NetDebtFinance	Net debt financing	Predictor	Bradshaw, Richardson, Sloan (2006)
NetEquityFinance	Net equity financing	Predictor	Bradshaw, Richardson, Sloan (2006)
NetPayoutYield	Net Payout Yield	Predictor	Boudoukh et al. (2007)
NetPayoutYield_q	Net Payout Yield quarterly	Placebo	Boudoukh et al. (2007)
PayoutYield	Payout Yield	Predictor	Boudoukh et al. (2007)
PayoutYield_q	Payout Yield quarterly	Placebo	Boudoukh et al. (2007)
ShareIss1Y	Share issuance (1 year)	Predictor	Pontiff and Woodgate (2008)
ShareIss5Y	Share issuance (5 year)	Predictor	Daniel and Titman (2006)
ShortInterest	Short Interest	Predictor	Dechow et al. (2001)
VolSD	Volume Variance	Predictor	Chordia, Subra, Anshuman (2001)
VolumeTrend	Volume Trend	Predictor	Haugen and Baker (1996)
XFIN	Net external financing	Predictor	Bradshaw, Richardson, Sloan (2006)
pchgm_pchsale	Change in gross margin vs sales	Placebo	Abarbanell and Bushee (1998)
realestate	Real estate holdings	Predictor	Tuzel (2010)
std_turn	Share turnover volatility	Predictor	Chordia, Subra, Anshuman (2001)
zerotrade1M	Days with zero trades	Predictor	Liu (2006)
zerotrade6M	Days with zero trades	Predictor	Liu (2006)
	Liquidity		
AgeIPO	IPO and age	Predictor	Ritter (1991)
Beta	CAPM beta	Predictor	Fama and MacBeth (1973)
BetaBDLeverage	Broker-Dealer Leverage Beta	Placebo	Adrian, Etula and Muir (2014)
BetaSquared	CAPM beta squred	Placebo	Fama and MacBeth (1973)
BetaTailRisk	Tail risk beta	Predictor	Kelly and Jiang (2014)
ChInvIA	Change in capital inv (ind adj)	Predictor	Abarbanell and Bushee (1998)
Coskewness	Coskewness	Predictor	Harvey and Siddique (2000)
DolVol	Past trading volume	Predictor	Brennan, Chordia, Subra (1998)
EarningsSmoothness	Earnings Smoothness	Placebo	Francis, LaFond, Olsson, Schipper (2004)
ForecastDispersionLT	Long-term forecast dispersion	Placebo	Anderson, Ghysels, and Juergens (2005)
Illiquidity	Amihud's illiquidity	Predictor	Amihud (2002)
Investment	Investment to revenue	Predictor	Titman, Wei and Xie (2004)
MeanRankRevGrowth	Revenue Growth Rank	Predictor	Lakonishok, Shleifer, Vishny (1994)

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Acronym	Description	Signal Type	Author
PredictedFE	Predicted Analyst forecast error	Predictor	Frankel and Lee (1998)
PriceDelayTstat	Price delay SE adjusted	Predictor	Hou and Moskowitz (2005)
VarCF	Cash-flow to price variance	Predictor	Haugen and Baker (1996)
VolMkt	Volume to market equity	Predictor	Haugen and Baker (1996)
WW_Q	Whited-Wu index	Placebo	Whited and Wu (2006)
betaCR	Illiquidity-market return beta (beta4i)	Placebo	Acharya and Pedersen (2005)
betaNet	Net liquidity beta (betanet,p)	Placebo	Acharya and Pedersen (2005)
betaRC	Return-market illiquidity beta	Placebo	Acharya and Pedersen (2005)
betaRR	Return-market return illiquidity beta	Placebo	Acharya and Pedersen (2005)
grcapx	Change in capex (two years)	Predictor	Anderson and Garcia-Feijoo (2006)
grcapx1y	Investment growth (1 year)	Placebo	Anderson and Garcia-Feijoo (2006)
grcapx3y	Change in capex (three years)	Predictor	Anderson and Garcia-Feijoo (2006)
pchdepr	Change in depreciation to PPE	Placebo	Holthausen and Larcker (1992)
zerotrade12M	Days with zero trades	Predictor	Liu (2006)
	Momentum		
AnalystRevision	EPS forecast revision	Predictor	Hawkins, Chamberlin, Daniel (1984)
AnnouncementReturn	Earnings announcement return	Predictor	Chan, Jegadeesh and Lakonishok (1996)
CoskewACX	Coskewness using daily returns	Predictor	Ang, Chen and Xing (2006)
CustomerMomentum	Customer momentum	Predictor	Cohen and Frazzini (2008)
DelBreadth	Breadth of ownership	Predictor	Chen, Hong and Stein (2002)
EarningsForecastDisparity	Long-vs-short EPS forecasts	Predictor	Da and Warachka (2011)
EarningsStreak	Earnings surprise streak	Predictor	Loh and Warachka (2012)
EarningsTimeliness	Earnings timeliness	Placebo	Francis, LaFond, Olsson, Schipper (2004)
EarningsValueRelevance	Value relevance of earnings	Placebo	Francis, LaFond, Olsson, Schipper (2004)
FirmAgeMom	Firm Age - Momentum	Predictor	Zhang (2006)
High52	52 week high	Predictor	George and Hwang (2004)
IndMom	Industry Momentum	Predictor	Grinblatt and Moskowitz (1999)
IndRetBig	Industry return of big firms	Predictor	Hou (2007)
IntMom	Intermediate Momentum	Predictor	Novy-Marx (2012)
Mom12m	Momentum (12 month)	Predictor	Jegadeesh and Titman (1993)
Mom12mOffSeason	Momentum without the seasonal part	Predictor	Heston and Sadka (2008)
Mom6m	Momentum (6 month)	Predictor	Jegadeesh and Titman (1993)
Mom6mJunk	Junk Stock Momentum	Predictor	Avramov et al (2007)
MomOffSeason11YrPlus	Off season reversal years 11 to 15	Predictor	Heston and Sadka (2008)
MomSeason11YrPlus	Return seasonality years 11 to 15	Predictor	Heston and Sadka (2008)
REV6	Earnings forecast revisions	Predictor	Chan, Jegadeesh and Lakonishok (1996)
ResidualMomentum	Momentum based on FF3 residuals	Predictor	Blitz, Huij and Martens (2011)
ResidualMomentum6m	6 month residual momentum	Placebo	Blitz, Huij and Martens (2011)
RevenueSurprise	Revenue Surprise	Predictor	Jegadeesh and Livnat (2006)
betaVIX	Systematic volatility	Predictor	Ang et al. (2006)
iomom_cust	Customers momentum	Predictor	Menzly and Ozbas (2010)
iomom_supp	Suppliers momentum	Predictor	Menzly and Ozbas (2010)
retConglomerate	Conglomerate return	Predictor	Cohen and Lou (2012)
	Profitability		
CBOperProf	Cash-based operating profitability	Predictor	Ball et al. (2016)
CBOperProfLagAT	Cash-based oper prof lagged assets	Placebo	Ball et al. (2016)
CBOperProfLagAT_q	Cash-based oper prof lagged assets qtrly	Placebo	Ball et al. (2016)
ChTax	Change in Taxes	Predictor	Thomas and Zhang (2011)
ChangeRoE	Change in Return on equity	Placebo	Balakrishnan, Bartov and Faurel (2010)
ETR	Effective Tax Rate	Placebo	Abarbanell and Bushee (1998)

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Acronym	Description	Signal Type	Author
EarningsConsistency	Earnings consistency	Predictor	Alwathainani (2009)
EarningsPersistence	Earnings persistence	Placebo	Francis, LaFond, Olsson, Schipper (2004)
EarningsPredictability	Earnings Predictability	Placebo	Francis, LaFond, Olsson, Schipper (2004)
GP	gross profits / total assets	Predictor	Novy-Marx (2013)
GPlag	gross profits / total assets	Placebo	Novy-Marx (2013)
GPlag_q	gross profits / total assets	Placebo	Novy-Marx (2013)
MomSeason	Return seasonality years 2 to 5	Predictor	Heston and Sadka (2008)
MomSeason06YrPlus	Return seasonality years 6 to 10	Predictor	Heston and Sadka (2008)
NumEarnIncrease	Earnings streak length	Predictor	Loh and Warachka (2012)
OperProfRD	Operating profitability R&D adjusted	Predictor	Ball et al. (2016)
OperProfRDLagAT	Oper prof R&D adj lagged assets	Placebo	Ball et al. (2016)
OperProfRDLagAT_q	Oper prof R&D adj lagged assets (qtrly)	Placebo	Ball et al. (2016)
OrgCap	Organizational capital	Predictor	Eisfeldt and Papanikolaou (2013)
OrgCapNoAdj	Org cap w/o industry adjustment	Placebo	Eisfeldt and Papanikolaou (2013)
PM	Profit Margin	Placebo	Soliman (2008)
PM_q	Profit Margin	Placebo	Soliman (2008)
RetNOA	Return on Net Operating Assets	Placebo	Soliman (2008)
RetNOA_q	Return on Net Operating Assets	Placebo	Soliman (2008)
Tax	Taxable income to income	Predictor	Lev and Nissim (2004)
Tax_q	Taxable income to income (qtrly)	Placebo	Lev and Nissim (2004)
cashdebt	CF to debt	Placebo	Ou and Penman (1989)
depr	Depreciation to PPE	Placebo	Holthausen and Larcker (1992)
roaq	Return on assets (qtrly)	Predictor	Balakrishnan, Bartov and Faurel (2010)
roic	Return on invested capital	Placebo	Brown and Rowe (2007)
	Value		
AM	Total assets to market	Predictor	Fama and French (1992)
AMq	Total assets to market (quarterly)	Placebo	Fama and French (1992)
AssetLiquidityMarket	Asset liquidity over market	Placebo	Ortiz-Molina and Phillips (2014)
AssetLiquidityMarketQuart	Asset liquidity over market (qtrly)	Placebo	Ortiz-Molina and Phillips (2014)
BM	Book to market, original (Stattman 1980)	Predictor	Stattman (1980)
BMdec	Book to market using December ME	Predictor	Fama and French (1992)
BMq	Book to market (quarterly)	Placebo	Rosenberg, Reid, and Lanstein (1985)
BetaLiquidityPS	Pastor-Stambaugh liquidity beta	Predictor	Pastor and Stambaugh (2003)
BookLeverage	Book leverage (annual)	Predictor	Fama and French (1992)
BookLeverageQuarterly	Book leverage (quarterly)	Placebo	Fama and French (1992)
CashProd	Cash Productivity	Predictor	Chandrashekar and Rao (2009)
EBM	Enterprise component of BM	Predictor	Penman, Richardson and Tuna (2007)
EBM_q	Enterprise component of BM	Placebo	Penman, Richardson and Tuna (2007)
EarningsConservatism	Earnings conservatism	Placebo	Francis, LaFond, Olsson, Schipper (2004)
Frontier	Efficient frontier index	Predictor	Nguyen and Swanson (2009)
IntanBM	Intangible return using BM	Predictor	Daniel and Titman (2006)
IntanCFP	Intangible return using CFtoP	Predictor	Daniel and Titman (2006)
IntanEP	Intangible return using EP	Predictor	Daniel and Titman (2006)
IntanSP	Intangible return using Sale2P	Predictor	Daniel and Titman (2006)
LRreversal	Long-run reversal	Predictor	De Bondt and Thaler (1985)
Leverage	Market leverage	Predictor	Bhandari (1988)
Leverage_q	Market leverage quarterly	Placebo	Bhandari (1988)
MRreversal	Medium-run reversal	Predictor	De Bondt and Thaler (1985)
MomOffSeason	Off season long-term reversal	Predictor	Heston and Sadka (2008)
MomSeasonShort	Return seasonality last year	Predictor	Heston and Sadka (2008)

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Acronym	Description	Signal Type	Author
RDS	Real dirty surplus	Predictor	Landsman et al. (2011)
TrendFactor	Trend Factor	Predictor	Han, Zhou, Zhu (2016)
ZScore	Altman Z-Score	Placebo	Dichev (1998)
ZScore_q	Altman Z-Score quarterly	Placebo	Dichev (1998)
cfpq	Operating Cash flows to price quarterly	Placebo	Desai, Rajgopal, Venkatachalam (2004)
	Volatility		
AccrualQuality	Accrual Quality	Placebo	Francis, LaFond, Olsson, Schipper (2005)
AccrualQualityJune	Accrual Quality in June	Placebo	Francis, LaFond, Olsson, Schipper (2005)
Activism2	Active shareholders	Predictor	Cremers and Nair (2005)
AnalystValue	Analyst Value	Predictor	Frankel and Lee (1998)
BetaDimson	Dimson Beta	Placebo	Dimson (1979)
BetaFP	Frazzini-Pedersen Beta	Predictor	Frazzini and Pedersen (2014)
BidAskSpread	Bid-ask spread	Predictor	Amihud and Mendelson (1986)
DelayAcct	Accounting component of price delay	Placebo	Callen, Khan and Lu (2013)
DownsideBeta	Downside beta	Placebo	Ang, Chen and Xing (2006)
FEPS	Analyst earnings per share	Predictor	Cen, Wei, and Zhang (2006)
FailureProbability	Failure probability	Placebo	Campbell, Hilscher and Szilagyi (2008)
FailureProbabilityJune	Failure probability	Placebo	Campbell, Hilscher and Szilagyi (2008)
ForecastDispersion	EPS Forecast Dispersion	Predictor	Diether, Malloy and Scherbina (2002)
IdioVol3F	Idiosyncratic risk (3 factor)	Predictor	Ang et al. (2006)
IdioVolAHT	Idiosyncratic risk (AHT)	Predictor	Ali, Hwang, and Trombley (2003)
IdioVolCAPM	Idiosyncratic risk (CAPM)	Placebo	Ang et al. (2006)
IdioVolQF	Idiosyncratic risk (q factor)	Placebo	Ang et al. (2006)
MaxRet	Maximum return over month	Predictor	Bali, Cakici, and Whitelaw (2011)
PriceDelayRsq	Price delay r square	Predictor	Hou and Moskowitz (2005)
PriceDelaySlope	Price delay coeff	Predictor	Hou and Moskowitz (2005)
RealizedVol	Realized (Total) Volatility	Predictor	Ang et al. (2006)
ReturnSkew	Return skewness	Predictor	Bali, Engle and Murray (2015)
WW	Whited-Wu index	Placebo	Whited and Wu (2006)
betaCC	Illiquidity-illiquidity beta (beta2i)	Placebo	Acharya and Pedersen (2005)
fgr5yrLag	Long-term EPS forecast	Predictor	La Porta (1996)
fgr5yrNoLag	Long-term EPS forecast (Monthly)	Placebo	La Porta (1996)
nanalyst	Number of analysts	Placebo	Elgers, Lo and Pfeiffer (2001)
roavol	RoA volatility	Placebo	Francis, LaFond, Olsson, Schipper (2004)
sfe	Earnings Forecast to price	Predictor	Elgers, Lo and Pfeiffer (2001)

Table 5: Conversion excess returns for single anomaly signals

We show equally-weighted long, short and long-short conversion excess returns of single anomalies. The signals are sorted into 10 groups. Conversion returns are multiplied by 100. Standard errors are adjusted according to Newey and West (1987). We show 153 predictors that we consider in our study and also 115 placebo. The sample covers the period from January 1996 to June 2021.

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
			Accruals			
AOP	0.05	0.32	0.09	0.51	-0.03	-4.64
AbnormalAccruals	0.21	1.57	0.20	1.50	0.01	1.08
AbnormalAccrualsPercent	-0.18	-1.67	-0.15	-1.40	-0.02	-4.10
Accruals	0.06	0.36	0.04	0.26	0.02	2.02
BPEBM	-0.08	-0.76	-0.12	-1.05	0.03	3.50
CF	0.57	1.26	0.53	1.17	0.04	2.48
CFq	0.72	1.62	0.64	1.44	0.08	5.74
ChNWC	0.08	0.82	0.08	0.79	0.00	0.60
EP	-0.03	-0.10	0.04	0.13	-0.07	-7.99
EPq	0.08	0.27	0.13	0.42	-0.05	-8.78
EntMult	0.23	0.55	0.29	0.68	-0.06	-6.72
EntMult_q	-0.19	-0.43	-0.22	-0.49	0.03	4.03
EquityDuration	0.56	1.56	0.52	1.44	0.04	2.96
ExclExp	0.19	1.15	0.19	1.20	-0.01	-1.58
IntrinsicValue	0.51	1.56	0.50	1.54	0.00	0.33
KZ	-0.12	-0.51	-0.15	-0.66	0.04	3.53
KZ_q	0.22	0.77	0.26	0.88	-0.03	-4.09
OperProf	0.66	1.60	0.64	1.56	0.01	1.51
OperProfLag	0.19	0.62	0.18	0.58	0.01	1.07
OperProfLag_q	0.94	2.51	0.88	2.34	0.06	5.86
PctAcc	0.39	3.02	0.35	2.67	0.04	4.71
RoE	0.71	2.28	0.66	2.12	0.05	4.25
SP	0.47	0.86	0.46	0.83	0.01	1.00
SP_q	0.51	0.95	0.50	0.93	0.01	0.66
cfp	0.72	1.84	0.67	1.70	0.05	3.62
currat	-0.27	-0.68	-0.32	-0.80	0.05	4.48
quick	-0.39	-0.84	-0.43	-0.92	0.04	3.27
rd_sale_q	-0.20	-0.42	-0.12	-0.25	-0.08	-4.34

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Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
salecash	0.67	1.43	0.62	1.31	0.05	4.26
secured	-0.12	-0.80	-0.12	-0.84	0.01	1.22
		Intangibles 1				
Activism1	-0.01	-0.04	-0.04	-0.11	0.02	2.76
AssetLiquidityBook	-0.19	-0.45	-0.15	-0.34	-0.05	-3.42
AssetLiquidityBookQuart	-0.29	-0.64	-0.25	-0.56	-0.04	-2.80
Cash	0.14	0.29	0.12	0.24	0.02	1.89
ChangeInRecommendation	0.14	1.71	0.14	1.69	-0.00	-0.18
Herf	0.31	0.84	0.31	0.82	0.00	0.59
HerfAsset	0.07	0.18	0.06	0.15	0.01	1.67
HerfBE	0.11	0.33	0.10	0.30	0.01	1.83
MomOffSeason16YrPlus	-0.13	-0.84	-0.10	-0.62	-0.03	-3.68
NOA	0.59	2.53	0.61	2.60	-0.02	-1.65
NetDebtPrice	-0.51	-1.17	-0.70	-1.60	0.19	10.04
NetDebtPrice_q	0.15	0.33	0.34	0.78	-0.19	-12.35
RD	-0.06	-0.14	-0.03	-0.07	-0.03	-1.80
RD_q	0.04	0.10	0.06	0.14	-0.02	-1.16
ReturnSkew3F	-0.09	-0.82	-0.11	-1.01	0.02	4.49
ReturnSkewCAPM	0.01	0.12	0.04	0.32	-0.02	-4.26
ReturnSkewQF	0.02	0.20	0.04	0.37	-0.02	-3.98
rd_sale	-0.19	-0.37	-0.12	-0.23	-0.07	-4.14
tang	-0.35	-0.85	-0.29	-0.70	-0.06	-3.36
tang_q	-0.08	-0.26	-0.04	-0.14	-0.04	-3.03
		Intangibles 2				
AdExp	0.11	0.22	0.21	0.42	-0.10	-8.16
AssetTurnover	0.81	3.87	0.71	3.45	0.09	8.36
AssetTurnover_q	0.81	4.03	0.72	3.60	0.09	8.46
BrandCapital	0.39	1.76	0.40	1.79	-0.00	-0.44
CapTurnover	0.50	2.28	0.41	1.90	0.09	7.95
CapTurnover_q	0.79	3.18	0.70	2.84	0.08	7.01
ChangeRoA	-0.04	-0.20	-0.08	-0.43	0.04	4.47
DelLTI	0.27	2.71	0.28	2.75	-0.00	-0.55

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Table 5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
DelSTI	0.03	0.27	0.04	0.32	-0.01	-0.81
DelayNonAcct	-0.16	-0.85	-0.11	-0.56	-0.05	-5.26
EarnSupBig	0.03	0.10	0.00	0.01	0.02	2.00
EarningsSurprise	-0.19	-1.67	-0.22	-1.88	0.02	4.60
FR	-0.24	-0.92	-0.29	-1.11	0.05	3.83
FRbook	-0.08	-0.55	-0.09	-0.58	0.00	0.46
OPLeverage	0.47	2.36	0.44	2.25	0.03	3.10
OPLeverage_q	0.51	2.66	0.49	2.55	0.02	2.87
OrderBacklog	-0.14	-0.63	-0.13	-0.57	-0.01	-1.27
pchcurrat	-0.12	-1.28	-0.13	-1.33	0.01	1.01
pchquick	-0.08	-0.78	-0.09	-0.94	0.02	2.43
salerec	0.43	2.17	0.40	2.02	0.03	3.25
			Investment			
AssetGrowth	0.61	2.81	0.63	2.91	-0.02	-2.39
AssetGrowth_q	-0.49	-1.97	-0.53	-2.12	0.04	3.58
ChAssetTurnover	-0.17	-1.47	-0.16	-1.35	-0.01	-1.85
ChEQ	0.56	2.86	0.59	3.02	-0.03	-4.17
ChInv	0.16	0.97	0.16	1.00	-0.00	-0.44
ChNCOA	-0.52	-2.38	-0.54	-2.46	0.02	2.14
ChNCOL	-0.20	-1.20	-0.22	-1.30	0.02	2.70
ChNNCOA	0.28	1.82	0.28	1.85	-0.00	-0.10
ChPM	-0.01	-0.04	-0.03	-0.19	0.02	2.87
DelCOA	0.11	0.79	0.13	0.89	-0.01	-2.21
DelCOL	-0.03	-0.15	-0.01	-0.05	-0.02	-2.78
DelEqu	0.56	2.75	0.61	2.94	-0.05	-4.92
GrAdExp	0.39	1.95	0.37	1.85	0.02	1.74
GrLTNOA	-0.14	-0.97	-0.15	-1.07	0.01	1.40
GrSaleToGrInv	0.08	0.63	0.07	0.57	0.01	1.26
GrSaleToGrOverhead	-0.26	-1.72	-0.26	-1.73	0.00	0.05
GrSaleToGrReceivables	0.11	0.84	0.12	0.93	-0.01	-1.72
InvGrowth	0.24	1.12	0.22	1.04	0.02	1.84
InvestPPEInv	0.52	2.61	0.51	2.59	0.01	0.94

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Table 5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
LaborforceEfficiency	-0.20	-1.60	-0.19	-1.57	-0.00	-0.59
OrderBacklogChg	0.06	0.27	0.03	0.13	0.03	2.56
PctTotAcc	0.15	1.18	0.15	1.25	-0.01	-1.68
TotalAccruals	0.16	1.05	0.20	1.28	-0.04	-4.66
dNoa	0.58	2.71	0.59	2.76	-0.01	-0.92
hire	0.37	1.68	0.38	1.75	-0.02	-2.35
pchsaleinv	-0.09	-0.59	-0.10	-0.64	0.01	1.18
saleinv	0.38	2.40	0.34	2.09	0.05	5.24
sgr	-0.43	-2.19	-0.44	-2.25	0.01	1.24
sgr_q	-0.22	-0.97	-0.25	-1.13	0.04	4.64
		Issuance				
CompEquIss	0.64	2.74	0.61	2.58	0.03	2.90
CompositeDebtIssuance	0.25	1.76	0.24	1.71	0.01	1.00
DelFINL	0.22	1.26	0.21	1.18	0.02	2.47
DelNetFin	0.13	0.81	0.10	0.61	0.03	4.88
FirmAge	-0.62	-1.66	-0.56	-1.49	-0.06	-4.97
GrGMToGrSales	0.32	2.46	0.27	2.11	0.05	4.11
MomOffSeason06YrPlus	0.17	0.88	0.19	1.03	-0.03	-3.25
MomSeason16YrPlus	0.38	2.46	0.38	2.43	0.00	0.46
NetDebtFinance	0.25	1.46	0.23	1.35	0.02	2.69
NetEquityFinance	0.83	2.56	0.78	2.39	0.05	4.00
NetPayoutYield	0.96	3.20	0.95	3.12	0.01	0.78
NetPayoutYield_q	0.65	2.04	0.64	2.00	0.01	0.90
PayoutYield	0.19	0.91	0.29	1.40	-0.10	-11.22
PayoutYield_q	0.46	2.58	0.52	2.92	-0.05	-8.54
ShareIss1Y	1.13	4.19	1.04	3.77	0.09	5.92
ShareIss5Y	0.94	4.19	0.87	3.91	0.06	4.21
ShortInterest	0.71	2.93	0.52	2.14	0.19	10.14
VolSD	0.30	1.01	0.26	0.89	0.03	1.95
VolumeTrend	0.72	2.82	0.63	2.50	0.08	5.60
XFIN	0.98	2.23	0.89	2.01	0.09	7.32
pchgm_pchsale	0.21	1.53	0.17	1.19	0.05	4.17

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Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
realestate	0.14	1.03	0.10	0.75	0.04	3.28
std_turn	1.43	2.61	1.03	1.90	0.40	7.34
zerotrade1M	0.35	0.80	0.29	0.67	0.05	3.02
zerotrade6M	0.46	1.00	0.40	0.87	0.06	3.20
		Liquidity				
AgeIPO	0.85	1.40	0.69	1.14	0.15	4.55
Beta	-0.41	-0.70	-0.40	-0.67	-0.02	-1.34
BetaBDLeverage	0.04	0.20	0.08	0.35	-0.03	-3.92
BetaSquared	0.48	0.81	0.45	0.76	0.02	1.95
BetaTailRisk	0.09	0.28	0.07	0.21	0.02	2.23
ChInvIA	0.21	1.23	0.20	1.17	0.01	1.02
Coskewness	0.30	1.27	0.26	1.11	0.04	4.83
DolVol	-0.60	-2.15	-0.48	-1.72	-0.12	-7.36
EarningsSmoothness	-0.02	-0.07	-0.05	-0.17	0.03	2.81
ForecastDispersionLT	-0.19	-0.54	-0.21	-0.57	0.01	2.19
Illiquidity	-0.68	-1.99	-0.52	-1.53	-0.15	-7.90
Investment	0.19	1.14	0.22	1.30	-0.03	-3.70
MeanRankRevGrowth	-0.27	-1.33	-0.22	-1.12	-0.04	-7.56
PredictedFE	-0.13	-0.43	-0.05	-0.18	-0.07	-10.25
PriceDelayTstat	0.09	0.54	0.09	0.53	0.00	0.24
VarCF	0.48	1.25	0.37	0.95	0.11	6.24
VolMkt	0.72	1.46	0.63	1.28	0.09	4.23
WW_Q	-0.46	-1.06	-0.40	-0.90	-0.07	-4.95
betaCR	0.25	1.28	0.17	0.88	0.08	6.21
betaNet	-0.47	-1.51	-0.40	-1.30	-0.06	-4.22
betaRC	-0.02	-0.06	-0.03	-0.08	0.01	0.61
betaRR	-0.22	-0.41	-0.21	-0.40	-0.01	-0.56
grcapx	0.49	2.57	0.51	2.71	-0.03	-2.89
grcapx1y	-0.05	-0.33	-0.06	-0.39	0.01	1.06
grcapx3y	0.39	2.22	0.43	2.41	-0.04	-3.44
pchdepr	0.05	0.38	0.06	0.45	-0.01	-1.15
zerotrade12M	0.47	1.05	0.42	0.92	0.05	2.88

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Table 5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
			Momentum			
AnalystRevision	0.10	0.61	0.08	0.54	0.01	2.32
AnnouncementReturn	0.45	2.97	0.42	2.77	0.03	3.91
CoskewACX	0.52	1.76	0.47	1.59	0.05	3.73
CustomerMomentum	0.33	1.24	0.30	1.14	0.02	2.09
DelBreadth	0.41	1.45	0.40	1.40	0.01	2.88
EarningsForecastDisparity	0.01	0.02	-0.01	-0.04	0.02	2.37
EarningsStreak	0.28	1.59	0.22	1.24	0.06	5.11
EarningsTimeliness	0.04	0.35	0.04	0.28	0.01	1.11
EarningsValueRelevance	0.21	2.01	0.21	2.03	-0.00	-0.06
FirmAgeMom	1.32	2.78	1.27	2.69	0.05	2.31
High52	1.29	2.65	1.14	2.32	0.15	7.04
IndMom	0.75	2.29	0.71	2.18	0.03	4.38
IndRetBig	0.67	2.20	0.64	2.12	0.03	2.54
IntMom	0.17	0.50	0.07	0.21	0.10	7.39
Mom12m	1.00	2.20	0.88	1.95	0.12	7.36
Mom12mOffSeason	1.02	2.65	0.95	2.46	0.07	4.57
Mom6m	1.37	3.62	1.30	3.40	0.07	5.15
Mom6mJunk	1.57	3.42	1.45	3.14	0.12	7.04
MomOffSeason11YrPlus	0.17	1.02	0.19	1.13	-0.02	-2.14
MomSeason11YrPlus	0.20	1.47	0.19	1.34	0.02	2.48
REV6	0.22	0.91	0.17	0.69	0.05	5.65
ResidualMomentum	0.51	1.80	0.48	1.69	0.03	3.44
ResidualMomentum6m	0.52	2.45	0.50	2.37	0.02	2.35
RevenueSurprise	0.11	0.75	0.10	0.68	0.01	2.41
betaVIX	0.28	1.56	0.28	1.51	0.01	1.16
iomom_cust	-0.01	-0.05	-0.03	-0.15	0.02	2.72
iomom_supp	0.23	1.17	0.22	1.12	0.01	1.69
retConglomerate	0.29	1.29	0.27	1.23	0.01	1.54
			Profitability			
CBOperProf	1.36	3.94	1.22	3.51	0.15	9.10
CBOperProfLagAT	1.13	4.28	1.00	3.78	0.13	9.10

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Table 5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
CBOperProfLagAT_q	1.02	3.78	0.92	3.41	0.10	7.66
ChTax	0.00	0.02	-0.02	-0.16	0.03	4.60
ChangeRoE	0.00	0.02	-0.03	-0.19	0.03	3.74
ETR	0.02	0.17	0.01	0.06	0.01	1.67
EarningsConsistency	0.24	1.17	0.20	0.98	0.04	3.27
EarningsPersistence	0.22	1.69	0.20	1.57	0.01	2.91
EarningsPredictability	-1.47	-4.59	-1.42	-4.44	-0.05	-5.29
GP	1.10	2.90	1.00	2.61	0.11	7.65
GPlag	0.55	2.18	0.46	1.83	0.09	7.29
GPlag_q	0.88	2.95	0.79	2.63	0.10	7.08
MomSeason	-0.01	-0.05	-0.02	-0.17	0.02	2.90
MomSeason06YrPlus	0.45	2.42	0.44	2.35	0.01	2.95
NumEarnIncrease	0.16	1.15	0.11	0.83	0.04	7.77
OperProfRD	1.35	3.11	1.22	2.77	0.14	7.90
OperProfRDLagAT	0.86	2.99	0.74	2.56	0.12	8.18
OperProfRDLagAT_q	1.36	3.55	1.22	3.18	0.14	8.46
OrgCap	0.14	0.71	0.15	0.75	-0.01	-0.90
OrgCapNoAdj	0.38	1.08	0.38	1.07	0.00	0.33
PM	0.50	1.17	0.42	0.98	0.08	5.88
PM_q	0.88	2.09	0.78	1.85	0.10	7.58
RetNOA	0.35	2.34	0.32	2.13	0.03	3.53
RetNOA_q	0.59	2.11	0.53	1.89	0.06	6.98
Tax	0.76	2.77	0.67	2.43	0.09	7.66
Tax_q	0.05	0.32	0.04	0.25	0.01	1.99
cashdebt	0.69	2.14	0.59	1.81	0.10	7.06
depr	0.13	0.46	0.07	0.23	0.06	6.51
roaq	0.79	2.18	0.68	1.85	0.11	7.85
roic	0.68	1.88	0.60	1.66	0.07	5.61
		Value				
AM	-0.17	-0.32	-0.10	-0.19	-0.06	-5.54
AMq	-0.34	-0.65	-0.28	-0.54	-0.06	-5.69
AssetLiquidityMarket	0.14	0.39	0.16	0.47	-0.03	-2.52

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Table 5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
AssetLiquidityMarketQuart	-0.03	-0.08	0.02	0.05	-0.05	-4.54
BM	0.13	0.35	0.17	0.47	-0.04	-4.13
BMdec	-0.03	-0.09	-0.01	-0.03	-0.02	-1.71
BMq	-0.46	-1.10	-0.41	-0.99	-0.05	-4.58
BetaLiquidityPS	-0.03	-0.15	-0.03	-0.15	-0.00	-0.11
BookLeverage	-0.33	-0.89	-0.32	-0.86	-0.01	-0.66
BookLeverageQuarterly	0.34	0.93	0.34	0.91	0.01	0.53
CashProd	-0.00	-0.01	0.06	0.19	-0.06	-6.37
EBM	-0.23	-1.57	-0.21	-1.43	-0.02	-3.32
EBM_q	-0.26	-1.61	-0.24	-1.50	-0.02	-2.67
EarningsConservatism	-0.04	-0.35	-0.05	-0.45	0.01	1.53
Frontier	-0.32	-0.78	-0.29	-0.72	-0.02	-2.04
IntanBM	0.13	0.36	0.20	0.55	-0.07	-4.70
IntanCFP	0.37	1.15	0.44	1.36	-0.07	-6.80
IntanEP	0.33	1.11	0.38	1.27	-0.05	-5.14
IntanSP	0.23	0.62	0.35	0.93	-0.12	-7.45
LRreversal	0.01	0.04	0.09	0.29	-0.08	-5.78
Leverage	0.05	0.09	0.10	0.20	-0.06	-4.86
Leverage_q	0.01	0.02	0.08	0.15	-0.07	-5.98
MRreversal	0.10	0.36	0.17	0.58	-0.06	-4.99
MomOffSeason	0.26	0.86	0.30	0.99	-0.04	-4.29
MomSeasonShort	-0.37	-1.43	-0.40	-1.53	0.03	4.46
RDS	0.01	0.04	0.04	0.24	-0.03	-6.63
TrendFactor	0.25	1.10	0.25	1.08	0.00	0.17
ZScore	-0.42	-0.95	-0.32	-0.73	-0.10	-5.48
ZScore_q	0.37	0.80	0.23	0.49	0.15	7.54
cfpq	0.81	2.42	0.75	2.24	0.05	4.89
		Volatility				
AccrualQuality	-0.42	-1.31	-0.41	-1.26	-0.01	-0.53
AccrualQualityJune	-0.42	-1.29	-0.41	-1.24	-0.01	-0.66
Activism2	1.10	2.52	1.08	2.53	0.01	0.47
AnalystValue	0.21	0.46	0.21	0.44	0.01	0.74

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Table 5 – continued from previous page

Acronym	r^{ls}_{stock}	t	r^{ls}_{F}	t	r^{ls}_{G}	t
BetaDimson	-0.21	-0.64	-0.19	-0.58	-0.02	-1.87
BetaFP	-0.27	-0.48	-0.24	-0.42	-0.04	-1.94
BidAskSpread	-1.17	-2.23	-1.00	-1.91	-0.16	-6.10
DelayAcct	-0.36	-1.61	-0.35	-1.56	-0.01	-0.86
DownsideBeta	-0.49	-0.82	-0.49	-0.82	0.00	0.13
FEPS	1.04	2.00	0.92	1.77	0.12	6.77
FailureProbability	0.83	1.50	0.68	1.23	0.15	6.63
FailureProbabilityJune	-0.91	-1.73	-0.77	-1.46	-0.14	-5.80
ForecastDispersion	0.67	1.94	0.62	1.79	0.05	5.73
IdioVol3F	1.17	2.30	1.02	1.98	0.15	6.53
IdioVolAHT	1.35	2.24	1.15	1.91	0.20	6.53
IdioVolCAPM	-1.14	-2.19	-0.99	-1.89	-0.15	-6.45
IdioVolQF	-1.37	-2.80	-1.22	-2.50	-0.14	-5.92
MaxRet	0.88	1.87	0.76	1.60	0.12	6.65
PriceDelayRsq	-0.66	-2.80	-0.51	-2.18	-0.15	-8.67
PriceDelaySlope	-0.52	-3.10	-0.45	-2.64	-0.07	-6.06
RealizedVol	1.04	1.92	0.90	1.66	0.14	6.02
ReturnSkew	0.05	0.46	0.03	0.22	0.03	5.12
WW	-0.62	-1.46	-0.55	-1.29	-0.06	-4.59
betaCC	-0.52	-2.67	-0.45	-2.34	-0.07	-4.80
fgr5yrLag	0.31	0.77	0.37	0.91	-0.06	-7.73
fgr5yrNoLag	-0.36	-0.72	-0.42	-0.85	0.06	8.44
nanalyst	0.82	3.25	0.67	2.65	0.15	10.03
roavol	-0.55	-1.23	-0.50	-1.11	-0.05	-3.08
sfe	0.46	0.90	0.39	0.75	0.07	3.11

Table 6: Semivariance premia for single anomaly signals
We show equally-weighted long, short and long-short semivariance premia of single anomalies. Semivariance premia are multiplied by 100. The signals are sorted into 10 groups. We show 153 predictor anomaly signals used in our main analysis and also 115 placebo anomaly signals. The sample covers the period from January 1996 to June 2021.

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
		Accurals		
AOP	0.04	2.41	-0.07	-5.16
AbnormalAccruals	-0.04	-4.95	0.05	4.71
AbnormalAccrualsPercent	-0.02	-2.21	0.04	8.49
Accruals	-0.03	-2.39	0.00	0.45
BPEBM	-0.05	-6.73	0.09	5.57
CF	0.14	4.73	-0.35	-18.79
CFq	0.14	6.00	-0.36	-16.74
ChNWC	0.00	0.61	-0.01	-0.77
EP	0.05	1.98	-0.05	-2.75
EPq	0.05	2.00	-0.04	-1.81
EntMult	0.08	2.75	-0.05	-2.64
EntMult_q	-0.09	-3.29	0.09	4.34
EquityDuration	0.15	7.55	-0.29	-15.15
ExclExp	0.03	7.71	-0.04	-2.34
IntrinsicValue	0.11	8.32	-0.26	-15.58
KZ	0.04	2.10	-0.00	-0.06
KZ_q	0.01	0.43	-0.11	-5.81
OperProf	0.13	6.40	-0.35	-16.55
OperProfLag	0.11	6.50	-0.33	-18.19
OperProfLag_q	0.13	8.85	-0.43	-26.78
PctAcc	0.05	4.22	-0.07	-8.36
RoE	0.13	10.09	-0.39	-31.79
SP	0.11	3.56	-0.21	-7.14
SP_q	0.11	3.62	-0.21	-7.23
cfp	0.11	4.36	-0.34	-20.13
currat	-0.16	-5.35	0.36	14.50
quick	-0.15	-5.28	0.38	14.26
rd_sale_q	-0.19	-9.39	0.56	26.52

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Table 6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
salecash	0.16	6.94	-0.36	-17.21
secured	-0.04	-5.14	0.14	10.74
		Intangibles 1		
Activism1	-0.11	-6.55	0.13	5.42
AssetLiquidityBook	-0.19	-10.06	0.38	30.48
AssetLiquidityBookQuart	-0.20	-7.74	0.43	21.13
Cash	-0.19	-6.36	0.39	17.16
ChangeInRecommendation	0.01	3.62	-0.01	-1.83
Herf	-0.13	-3.80	0.23	7.81
HerfAsset	-0.12	-3.96	0.25	7.09
HerfBE	-0.09	-3.48	0.21	6.46
MomOffSeason16YrPlus	0.01	0.65	0.03	1.20
NOA	-0.04	-3.66	0.11	3.39
NetDebtPrice	-0.01	-0.34	0.11	4.56
NetDebtPrice_q	-0.01	-0.25	-0.08	-3.63
RD	-0.14	-8.82	0.33	14.16
RD_q	-0.14	-9.00	0.35	13.75
ReturnSkew3F	0.02	5.86	-0.08	-11.90
ReturnSkewCAPM	-0.02	-5.20	0.08	10.85
ReturnSkewQF	-0.02	-5.76	0.07	11.48
rd_sale	-0.20	-7.93	0.60	23.72
tang	-0.19	-10.24	0.47	27.49
tang_q	-0.14	-20.41	0.24	18.93
		Intangibles 2		
AdExp	0.03	0.81	0.05	1.67
AssetTurnover	-0.04	-1.87	-0.03	-2.18
AssetTurnover_q	-0.02	-1.17	-0.05	-2.66
BrandCapital	-0.09	-4.30	0.03	1.07
CapTurnover	-0.03	-2.52	-0.12	-3.93
CapTurnover_q	-0.01	-0.63	-0.18	-6.79
ChangeRoA	0.00	0.46	-0.02	-1.78
DelLTI	-0.02	-2.60	0.03	2.10

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Table 6 – continued from previous page

Acronym	VP^{+}_{ls}	t	VP^{-}_{ls}	t
DelSTI	0.02	1.97	0.01	0.77
DelayNonAcct	0.04	1.73	0.14	4.40
EarnSupBig	0.02	2.00	-0.04	-2.28
EarningsSurprise	0.00	0.44	-0.01	-1.97
FR	0.08	7.06	-0.14	-8.91
FRbook	0.05	5.59	-0.08	-4.22
OPLeverage	-0.09	-6.37	0.06	2.61
OPLeverage_q	-0.07	-4.66	0.05	2.51
OrderBacklog	-0.02	-1.41	0.10	4.48
pchcurrat	0.01	1.88	-0.02	-1.86
pchquick	0.01	2.23	-0.02	-1.79
salerec	-0.06	-8.02	0.03	1.25
		Investment		
AssetGrowth	0.01	0.69	0.03	1.32
AssetGrowth_q	-0.00	-0.20	-0.04	-2.27
ChAssetTurnover	-0.01	-0.92	0.00	0.46
ChEQ	-0.00	-0.03	0.03	1.35
ChInv	0.02	1.71	0.01	0.64
ChNCOA	-0.01	-0.46	-0.04	-2.39
ChNCOL	-0.02	-1.24	-0.02	-0.94
ChNNCOA	0.00	0.32	0.02	2.20
ChPM	0.00	0.13	-0.02	-1.83
DelCOA	0.04	3.35	-0.03	-3.18
DelCOL	0.06	4.64	-0.03	-2.79
DelEqu	0.01	0.30	0.05	2.32
GrAdExp	0.04	2.85	-0.03	-2.07
GrLTNOA	-0.01	-0.88	-0.01	-0.81
GrSaleToGrInv	-0.01	-1.09	0.02	1.20
GrSaleToGrOverhead	-0.02	-2.12	0.01	0.56
GrSaleToGrReceivables	-0.01	-1.41	0.02	2.59
InvGrowth	0.02	2.14	-0.04	-2.60
InvestPPEInv	0.03	2.38	0.02	0.92

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Table 6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
LaborforceEfficiency	-0.01	-1.66	0.01	0.65
OrderBacklogChg	0.01	0.48	-0.01	-0.55
PctTotAcc	0.00	0.65	-0.03	-2.28
TotalAccruals	-0.03	-2.19	0.10	9.68
dNoa	-0.01	-0.67	0.05	3.70
hire	0.05	2.76	-0.05	-2.62
pchsaleinv	-0.00	-0.43	0.00	0.36
saleinv	0.06	8.29	-0.11	-9.85
sgr	-0.05	-3.51	0.04	3.22
sgr_q	-0.02	-1.95	0.00	0.46
		Issuance		
CompEquIss	-0.02	-1.08	-0.23	-10.22
CompositeDebtIssuance	0.03	5.38	-0.01	-0.91
DelFINL	0.03	3.93	-0.02	-1.77
DelNetFin	-0.01	-0.56	0.01	0.57
FirmAge	-0.14	-6.30	0.45	19.33
GrGMToGrSales	0.01	1.78	-0.06	-4.86
MomOffSeason06YrPlus	0.07	4.58	0.03	1.83
MomSeason16YrPlus	0.01	1.78	-0.04	-4.29
NetDebtFinance	0.03	4.06	-0.02	-1.73
NetEquityFinance	0.15	7.91	-0.43	-23.07
NetPayoutYield	0.15	6.02	-0.40	-20.45
NetPayoutYield_q	0.16	6.61	-0.37	-17.29
PayoutYield	0.07	2.96	-0.08	-5.32
PayoutYield_q	0.08	8.33	-0.15	-10.55
ShareIss1Y	0.12	10.19	-0.35	-14.32
ShareIss5Y	0.11	7.85	-0.35	-19.06
ShortInterest	0.18	22.67	-0.19	-7.51
VolSD	0.21	9.43	0.16	3.35
VolumeTrend	0.08	4.09	-0.06	-2.44
XFIN	0.15	7.33	-0.41	-17.78
pchgm_pchsale	0.01	1.78	-0.05	-4.50

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Table 6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
realestate	0.00	0.78	-0.06	-3.31
std_turn	0.17	5.38	0.06	1.20
zerotrade1M	0.26	9.16	-0.04	-0.68
zerotrade6M	0.27	9.09	-0.06	-0.85
		Liquidity		
AgeIPO	0.15	7.78	-0.30	-9.08
Beta	-0.32	-9.19	0.44	10.28
BetaBDLeverage	0.02	1.39	0.00	0.08
BetaSquared	0.32	9.80	-0.44	-10.23
BetaTailRisk	-0.21	-13.16	0.27	13.33
ChInvIA	0.01	0.82	-0.02	-1.38
Coskewness	0.02	1.65	-0.05	-1.99
DolVol	0.05	2.73	0.59	17.54
EarningsSmoothness	-0.12	-10.03	0.13	2.81
ForecastDispersionLT	-0.17	-10.43	0.16	5.12
Illiquidity	-0.06	-4.11	0.72	27.06
Investment	-0.02	-2.04	0.10	8.25
MeanRankRevGrowth	0.07	2.87	-0.01	-0.59
PredictedFE	0.17	4.03	-0.17	-5.56
PriceDelayTstat	0.07	6.85	-0.08	-6.04
VarCF	0.15	7.02	-0.39	-24.33
VolMkt	0.28	9.78	-0.12	-1.48
WW_Q	-0.17	-7.24	0.75	30.00
betaCR	0.03	5.76	-0.24	-6.57
betaNet	-0.11	-9.52	0.39	12.00
betaRC	0.13	5.66	-0.22	-7.35
betaRR	-0.28	-8.03	0.32	8.77
grcapx	0.04	1.87	-0.01	-0.36
grcapx1y	-0.03	-1.71	0.01	0.67
grcapx3y	0.02	1.14	0.05	2.21
pchdepr	-0.01	-0.81	0.03	2.08
zerotrade12M	0.27	8.81	-0.05	-0.66

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Table 6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
		Momentum		
AnalystRevision	0.01	2.05	-0.03	-5.99
AnnouncementReturn	-0.00	-0.32	-0.02	-2.21
CoskewACX	0.03	1.57	-0.05	-1.37
CustomerMomentum	0.02	3.67	-0.02	-2.99
DelBreadth	-0.01	-0.76	-0.01	-0.69
EarningsForecastDisparity	0.03	2.52	-0.05	-4.46
EarningsStreak	0.00	0.25	-0.09	-5.81
EarningsTimeliness	-0.02	-4.61	0.03	1.13
EarningsValueRelevance	0.00	0.58	-0.05	-3.55
FirmAgeMom	-0.04	-2.01	-0.07	-2.76
High52	0.18	9.66	-0.35	-13.75
IndMom	-0.01	-0.48	0.03	1.39
IndRetBig	0.01	0.76	0.02	1.81
IntMom	0.01	0.85	-0.10	-5.59
Mom12m	0.02	1.12	-0.16	-6.13
Mom12mOffSeason	-0.04	-2.06	-0.05	-1.85
Mom6m	0.01	0.79	-0.12	-5.05
Mom6mJunk	0.04	1.84	-0.16	-5.41
MomOffSeason11YrPlus	0.02	1.83	0.11	6.41
MomSeason11YrPlus	0.00	0.99	-0.06	-10.78
REV6	0.02	1.61	-0.03	-2.12
ResidualMomentum	0.02	1.94	-0.06	-3.07
ResidualMomentum6m	0.03	2.95	-0.06	-3.67
RevenueSurprise	0.00	0.41	-0.00	-0.33
betaVIX	0.02	3.42	-0.04	-3.82
iomom_cust	0.02	2.52	-0.03	-3.82
iomom_supp	0.01	0.89	-0.01	-1.01
retConglomerate	0.03	2.73	-0.02	-1.52
		Profitability		
CBOperProf	0.08	7.70	-0.41	-19.47
CBOperProfLagAT	0.04	2.54	-0.38	-15.68

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Table 6 – continued from previous page

Acronym	VP^{+}_{ls}	t	VP^{-}_{ls}	t
CBOperProfLagAT_q	0.04	3.99	-0.27	-15.34
ChTax	-0.01	-1.33	-0.03	-3.52
ChangeRoE	0.01	2.13	-0.04	-4.75
ETR	0.02	3.17	-0.03	-4.59
EarningsConsistency	0.06	5.26	-0.15	-11.59
EarningsPersistence	-0.00	-0.43	-0.15	-12.89
EarningsPredictability	-0.12	-4.73	0.16	5.18
GP	0.07	6.97	-0.32	-13.00
GPlag	-0.01	-0.35	-0.19	-9.73
GPlag_q	0.05	4.35	-0.27	-15.46
MomSeason	-0.01	-1.43	-0.03	-3.20
MomSeason06YrPlus	-0.01	-2.78	-0.04	-7.07
NumEarnIncrease	0.03	5.66	-0.10	-13.06
OperProfRD	0.08	5.63	-0.41	-19.02
OperProfRDLagAT	-0.00	-0.08	-0.27	-8.43
OperProfRDLagAT_q	0.06	3.93	-0.36	-20.30
OrgCap	-0.03	-3.09	0.12	7.06
OrgCapNoAdj	-0.01	-0.58	0.22	13.84
PM	0.17	11.91	-0.43	-27.83
PM_q	0.14	14.25	-0.47	-29.17
RetNOA	0.02	1.43	-0.12	-5.61
RetNOA_q	0.07	8.27	-0.25	-10.43
Tax	0.06	5.69	-0.26	-14.52
Tax_q	0.05	6.04	-0.06	-3.60
cashdebt	0.12	12.19	-0.41	-37.38
depr	-0.12	-4.24	0.19	7.98
roaq	0.13	11.07	-0.49	-24.15
roic	0.13	12.32	-0.47	-32.03
		Value		
AM	0.13	4.03	-0.11	-3.83
AMq	0.13	4.09	-0.10	-3.54
AssetLiquidityMarket	-0.03	-1.24	0.15	4.65

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Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
AssetLiquidityMarketQuart	-0.03	-0.86	0.16	6.10
BM	0.01	0.27	0.12	4.72
BMdec	0.09	3.63	-0.06	-2.62
BMq	0.04	1.67	0.08	3.97
BetaLiquidityPS	-0.01	-0.90	-0.00	-0.14
BookLeverage	-0.12	-4.55	0.26	6.79
BookLeverageQuarterly	0.12	4.69	-0.26	-6.27
CashProd	0.06	4.39	0.10	4.42
EBM	-0.04	-7.09	0.12	11.95
EBM_q	-0.04	-7.73	0.13	13.79
EarningsConservatism	-0.00	-0.30	0.00	0.61
Frontier	0.02	0.89	0.20	8.58
IntanBM	-0.04	-2.24	0.16	6.58
IntanCFP	0.02	0.79	0.05	1.72
IntanEP	0.03	1.24	0.06	2.24
IntanSP	-0.07	-2.45	0.29	11.66
LRreversal	-0.03	-1.09	0.15	5.48
Leverage	0.15	4.30	-0.18	-5.12
Leverage_q	0.14	4.19	-0.18	-5.03
MRreversal	-0.02	-1.03	0.08	4.78
MomOffSeason	0.08	2.80	-0.00	-0.10
MomSeasonShort	0.01	0.74	-0.04	-4.80
RDS	-0.00	-0.05	0.11	6.25
TrendFactor	-0.01	-1.29	0.01	0.59
ZScore	0.00	0.12	0.09	2.35
ZScore_q	0.01	0.16	-0.10	-2.64
cfpq	0.07	5.17	-0.23	-13.24
		Volatility		
AccrualQuality	-0.20	-9.70	0.39	24.13
AccrualQualityJune	-0.19	-9.03	0.39	23.98
Activism2	-0.00	-0.07	0.04	1.69
AnalystValue	0.12	6.74	-0.32	-12.09

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Table 6 – continued from previous page

Acronym	VP_{ls}^{+}	t	VP_{ls}^{-}	t
BetaDimson	-0.16	-8.19	0.14	5.75
BetaFP	-0.38	-10.01	0.33	10.54
BidAskSpread	-0.32	-15.38	0.67	39.61
DelayAcct	-0.11	-3.94	0.25	5.35
DownsideBeta	-0.30	-9.11	0.30	8.13
FEPS	0.21	9.88	-0.72	-32.80
FailureProbability	0.36	14.34	-0.71	-43.20
FailureProbabilityJune	-0.32	-12.34	0.66	41.63
ForecastDispersion	0.16	21.02	-0.38	-25.43
IdioVol3F	0.36	14.31	-0.64	-28.71
IdioVolAHT	0.40	14.05	-0.76	-40.72
IdioVolCAPM	-0.36	-14.63	0.65	28.73
IdioVolQF	-0.35	-13.47	0.64	27.19
MaxRet	0.33	13.36	-0.55	-25.49
PriceDelayRsq	-0.05	-2.18	0.37	8.57
PriceDelaySlope	-0.04	-4.00	0.15	7.70
RealizedVol	0.39	14.87	-0.62	-29.25
ReturnSkew	0.03	6.90	-0.10	-10.63
WW	-0.16	-7.49	0.76	28.24
betaCC	-0.05	-4.24	0.30	9.03
fgr5yrLag	0.19	4.23	-0.27	-6.56
fgr5yrNoLag	-0.18	-3.68	0.26	5.47
nanalyst	0.01	0.30	-0.54	-20.04
roavol	-0.23	-12.05	0.44	10.65
sfe	0.17	7.46	-0.41	-12.16

Appendix A Cluster algorithm

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

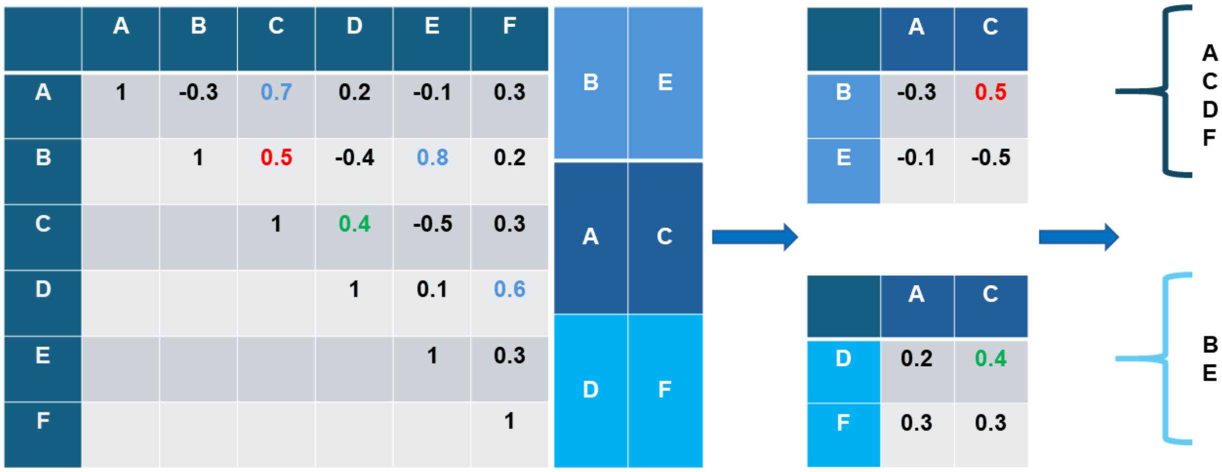
To group the signals, we iterate over all signal pairs, starting with the pair with the highest correlation and proceeding in descending order. In general, signals with high correlation are grouped into the same cluster. More specifically, each signal initially belongs to a separate cluster. During the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

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

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

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

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



References

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

Arnott, R.D., Harvey, C.R., Kalesnik, V., Linnainmaa, J.T., 2021. Reports of value's death may be greatly exaggerated. Financial Analysts Journal 77, 44–67.

Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies 16, 101–143.

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.

Bekaert, G., Hoerova, M., 2014. The vix, the variance premium and stock market volatility. Journal of econometrics 183, 181–192.

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.

Black, F., 1975. Fact and fantasy in the use of options. Financial Analysts Journal 31, 36–41.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of political economy 81, 637–654.

Böll, J., Meng, F., Thimme, J., Uhrig-Homburg, M., 2024. Following the footprints: Towards a taxonomy of the factor zoo. Available at SSRN 4702435 .

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

Brunnermeier, M.K., Pedersen, L.H., 2009. Market liquidity and funding liquidity. The review of financial studies 22, 2201–2238.

Carr, P., Madan, D., 2001. Optimal positioning in derivative securities. Quantitative Finance 1, 19–37.

Carr, P., Wu, L., 2009. Variance risk premiums. The Review of Financial Studies 22, 1311–1341.

Chang, B.Y., Christoffersen, P., Jacobs, K., Vainberg, G., 2012. Option-implied measures of equity risk. Review of Finance 16, 385–428.

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

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

Cremers, M., Weinbaum, D., 2010. Deviations from put-call parity and stock return predictability. Journal of Financial and Quantitative Analysis 45, 335–367.

Da, Z., Dong, X., Wu, K., Zhou, D., 2024. Inside and outside informed trading. Available on https://dzfinance.notion.site/Research-b6e809c020594c56aa28f0526f87d607 .

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.

Diamond, D.W., Verrecchia, R.E., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of financial economics 18, 277–311.

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

Frazzini, A., Pedersen, L.H., 2022. Embedded leverage. The Review of Asset Pricing Studies 12, 1–52.

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

Götz, A., Riordan, R., Schuster, P., Uhrig-Homburg, M., 2025. Measuring option liquidity. Working Paper.

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

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

Han, Y., Huang, D., Xiao, X., 2024. Options traders, reversals, and stock returns. Reversals, and Stock Returns (September 15, 2024) .

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

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

He, Z., Krishnamurthy, A., 2013. Intermediary asset pricing. American Economic Review 103, 732–770.

Held, M., Kapraun, J., Omachel, M., Thimme, J., 2020. Up-and downside variance risk premia in global equity markets. Journal of Banking & Finance 118, 105875.

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

Hollstein, F., Simen, C.W., 2020. Variance risk: A bird's eye view. Journal of Econometrics 215, 517–535.

Hollstein, F., Wese Simen, C., 2024. How do investors trade option anomalies? How do Investors Trade Option Anomalies .

Jacobs, K., Mai, A.T., Pederzoli, P., 2024. Identifying demand curves in index option markets. SSRN .

Jiang, G.J., Tian, Y.S., 2005. The model-free implied volatility and its information content. The Review of Financial Studies 18, 1305–1342.

Kilic, M., Shaliastovich, I., 2019. Good and bad variance premia and expected returns. Management Science 65, 2522–2544.

McLean, R.D., Pontiff, J., Reilly, C., 2020. Taking sides on return predictability. Available at SSRN 3637649 .

Muravyev, D., Pearson, N.D., 2020. Options trading costs are lower than you think. The Review of Financial Studies 33, 4973–5014.

Muravyev, D., Pearson, N.D., Pollet, J.M., 2023. 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.

Sorescu, S.M., 2000. The effect of options on stock prices: 1973 to 1995. Journal of Finance 55, 487–514.