# Options on Drugs: Industry Exposure and Option Anomalies*

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May 2025

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On average, writing options on pharmaceutical stocks yields higher returns than writing options on stocks in any other industry. The exposure to options on pharmaceuticals helps explain the persistent returns of delta-hedged option strategies, such as sorting options based on corporate cash holdings. Pharmaceutical stocks exhibit high growth potential and unique lottery features related to drug trials and development, leading to increased demand for their option contracts. Furthermore, the biotechnology bubble of the early 2000s inhibits common option risk factors from fully capturing the returns of pharmaceutical options.

*JEL classification*: G12, G14

*Keywords*: Options; Option anomalies; Cross-section of option returns; Industry exposure

*I am grateful to Can Gao, Jens Jackwerth, Mathis Mörke, Stephan Sontheimer (discussant), Christian Wagner, Tobias Wiest, and seminar participants at the University of Konstanz for their constructive and insightful comments.

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# Options on Drugs:
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**Abstract**

On average, writing options on pharmaceutical stocks yields higher returns than writing options on stocks in any other industry. The exposure to options on pharmaceuticals helps explain the persistent returns of delta-hedged option strategies, such as sorting options based on corporate cash holdings. Pharmaceutical stocks exhibit high growth potential and unique lottery features related to drug trials and development, leading to increased demand for their option contracts. Furthermore, the biotechnology bubble of the early 2000s inhibits common option risk factors from fully capturing the returns of pharmaceutical options.

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## 1. Introduction

Empirical research on equity options documents significant long-short portfolio returns when sorting delta-neutral positions on arbitrary characteristics at the underlying stock level. Notably, Zhan, Han, Cao, and Tong (2022) are the first to provide a detailed analysis of these return puzzles based on variables such as corporate cash holdings and profitability.[1] A compelling argument that can explain cross-sectional effects in option returns relates to the distinct features of the options market. First, risks to market making and practical limitations, like jump risk and hedging costs, can explain return premiums demanded by option writers (Figlewski, 1989; Tian & Wu, 2023). Second, demand pressure amplifies this effect as market makers are exposed to increased unhedgeable risks under strong order imbalances (Garleanu, Pedersen, & Poteshman, 2009). Consequently, if stock characteristics relate to properties indicative of higher hedging costs or lead to excessive end-user demand, sorting on these variables can lead to strong predictability in the cross-section of option returns. In this context, Cao and Han (2013) argue that idiosyncratic volatility of the underlying stock strongly reflects market-making costs, which is a reason why an option factor based on idiosyncratic volatility captures the option anomalies in Zhan et al. (2022). Likewise, Käfer, Moerke, Weigert, and Wiest (2025) identify historical jump risk of the underlying stock, which also constitutes a key determinant of arbitrage costs in the options markets, as a highly likely part of the SDF that prices long-short option portfolios.

However, despite these solid arguments founded on the options market structure, open questions remain in empirical options research. In particular, some option anomalies remain robust to controlling for option risk factors, and the relationship between option market risks and some anomaly characteristics is not trivial. One of the most prominent and persistent option anomalies is based on corporate cash holdings, with options written on high-cash firms yielding significantly positive returns. O'Donovan and Yu (2024) show that the cash anomaly is among the few option anomalies that stay significant after transaction costs, and Horenstein et al. (2024) demonstrate how it contributes to explaining option returns based on more than 100 sorting characteristics.

In this paper, I leverage a simple approach to enhance the understanding of the cross-section of delta-hedged returns. At its core, this paper is motivated by the observation of stark

[1] Although Duarte, Jones, Mo, and Khorram (2024) point out that the original study by Zhan et al. (2022) suffers from look-ahead bias in their sample construction that inflates option returns, other contributions like Goyal and Saretto (2024); Horenstein, Vasquez, and Xiao (2024), and this paper included, reaffirm the weaker but still existent cross-sectional predictability related to these variables.

differences in average option returns across industries of the underlying stock. Figure 1 plots the average monthly mean return by Fama-French 49 industry from the perspective of a call option writer. For both initial and daily hedging approaches aiming to isolate the return on the option from movements in the underlying stock, options on pharmaceuticals (industry code 13, "Drugs") yield by far the highest and most significant returns, whereas writing options on stocks in most other sectors tends to yield no return significantly different from zero on average.

To my knowledge, the differences in option returns across industries are not extensively studied in the existing literature, particularly the strong performance of writing options on pharmaceuticals, which provides an intriguing starting point for investigation in itself.[2] In various analyses throughout this paper, I assess the extent to which option strategy returns are driven by the exposure to options on pharmaceuticals. Crucially, analyzing industry concentration in option portfolios can facilitate the comprehension of cross-sectional return effects. My results show that exposure to pharmaceutical options accounts for the profitability of option strategies, like firm cash holdings, which are based on characteristics typical of pharmaceutical firms. Moreover, controlling for an option pharmaceutical factor, which is long in options on pharmaceutical stocks and short in all other options, reduces the significance of dozens of options strategies on its own. Adding the pharmaceutical factor to established option risk factors enhances the factor model's ability to price option strategies. Although option strategies exhibiting a considerable exposure to any industry are not per se problematic, it is essential to address "sector bets" in the options market, given the sheer abundance of seemingly profitable strategies. Sorting based on characteristics indicative of pharmaceuticals can give rise to the impression of an own factor "zoo" for option returns (see Cochrane, 2011), or at the very least exaggerate the size of it. Especially when jointly controlling for common option risk factors and the exposure to pharmaceutical options, the cross-section of option returns is not characterized by a zoo of abnormal returns but rather by a single pharmaceutical anomaly.

I begin my empirical analyses by focusing on the ten option anomaly characteristics examined by Zhan et al. (2022) over the period from 1996 to 2022. Controlling for risks to market-making and other option risks by using the factors introduced in Tian and Wu (2023) and the idiosyncratic volatility of the underlying stock (Cao & Han, 2013; Zhan et al., 2022), I can account for most of the abnormal options returns of these ten anomalies. The notable

[2]Only two notable papers on option returns address the impact of the pharmaceutical sector: Cao, Han, Li, Yang, and Zhan (2024) and Wang (2024). They focus on forecasting option returns with news and machine learning methods, whereas I focus on structured data and the related cross-sectional option anomalies.

exception is a long-short portfolio based on firm cash holdings that maintains a statistically significant alpha over the option risk factors. In the subsequent analysis of industry exposure in anomalies' high and low portfolios, I demonstrate that the cash anomaly's long portfolio exhibits a 42 percentage point higher share in options on pharmaceutical stocks compared to the short portfolio. Other anomalies heavily skewed regarding the industry exposure to pharmaceuticals are the two profitability measures, profit margin and operating profitability.

In the next part of my empirical analyses, I construct the simple pharmaceutical option factor to control for the exposure of option anomalies to options on pharmaceuticals. The factor yields highly significant returns of 1.1% per month. Controlling for option risk factors does not eliminate the pharmaceutical factor's significant regression alphas. Interestingly, the pharmaceutical factor loads most heavily on the historical option risk premium, which is constructed based on an option momentum signal introduced by Heston, Jones, Khorram, Li, and Mo (2023). The strong relation between the pharmaceutical factor and option momentum effects indicates the persistent return premium that options on pharmaceuticals demand. Regressing option anomaly returns on the pharmaceutical factor eliminates the statistical significance of the cash holding anomaly. Mean returns of other anomaly characteristics tend to remain significant but reduce by roughly 50% in magnitude. Combining the pharmaceutical factor with industry-*demeaned* options risk factors fully explains the remaining anomaly profits. I consider industry-adjusted risk factors to account for these factors being overly exposed to pharmaceutical options.

My baseline analysis suggests that comparatively large cash holdings characterize pharmaceutical stocks. Previous literature on corporate cash holdings indicates that firms with considerable growth potential accumulate higher cash reserves under a precautionary savings motive to invest in profitable investment opportunities when alternative outside funding is challenging to obtain (Bates, Kahle, & Stulz, 2009; Opler, Pinkowitz, Stulz, & Williamson, 1999). Firms with elevated growth potential and cash holdings typically have high R&D expenditures and intangible assets (Begenau & Palazzo, 2021; Falato, Kadyrzhanova, Sim, & Steri, 2022). Pharmaceuticals are prime examples of such firms. Therefore, the observation of high returns on options on pharmaceuticals aligns with Andreou, Bali, Kagkadis, and Lambertides (2024), who document the overvaluation of options written on stocks with high growth potential. I verify that pharmaceuticals indeed display by far higher values of future growth opportunities than other stocks, and are further characterized by large values of related variables such as

R&D intensity. Again, regressing option strategies based on growth potential variables on the pharmaceutical option factor explains their significant returns. At the same time, similar to the cash anomaly, controlling for option risk factors alone is insufficient to explain these option anomalies. Hence, my results indicate that the results in Andreou et al. (2024) are, at least to a large extent, driven by options on pharmaceuticals.

Next, I generalize my results to 140 option anomaly strategies based on stock characteristics from Jensen, Kelly, and Pedersen (2023). I confirm the presence of an option anomaly zoo with roughly half of these strategies formed on arbitrary characteristics exhibiting an absolute $t$-statistic above 3. Controlling for the pharmaceutical factor alone reduces the number of significant sorting strategies by half. Combining the pharmaceutical factor with industry-demeaned risk factors eliminates the significance of all but a handful of strategies. Including the pharmaceutical factor incrementally improves the pricing performance of option factors, especially for anomalies and sorting characteristics with a higher exposure to the pharmaceutical industry. Clusters of such stock-level characteristics are *Value*, *Profitability*, and *Low Leverage*, as pharmaceuticals tend to exhibit high valuation ratios, low profitability, and low asset tangibility.

In the final section of this paper, I examine the features of pharmaceutical stocks and their options in more detail. I show that options on pharmaceuticals are associated with higher option demand pressure as proxied by open interest, option volume, and signed open interest. Using news data from RavenPack News Analytics, I link pharmaceutical firms' large stock jump surprises to drug trials and development events. Furthermore, I provide tentative evidence that investors' overreaction to news on positive jump days leads to overvaluation in pharmaceutical options, in line with lottery preferences of option investors (Andreou et al., 2024; Byun & Kim, 2016). Finally, I outline distinct patterns in the time series of options on pharmaceuticals. The bubble and elevated volatility in biotechnology stocks at the beginning of the 2000s contribute to the low explanatory power of option risk factors for returns on pharmaceutical options.

**Related literature.** First and foremost, this paper adds to the literature on the return predictability in the cross-section of equity options. Various contributions study the relationship between delta-hedged returns and different stock-level characteristics, starting with Goyal and Saretto (2009) and the difference between implied and realized volatility. Other notable examples include, Cao and Han (2013) for idiosyncratic volatility, Byun and Kim (2016) for lottery characteristics, Vasquez (2017) for the term structure of implied volatility, Ruan (2020) and Cao, Vasquez, Xiao, and Zhan (2023) for volatility-of-volatility, Ramachandran and Tayal

(2021) for short sale constraints, Choy and Wei (2023) for investor attention, Vasquez and Xiao (2024) for firm default risk, and Cao, Goyal, Zhan, and Zhang (2024) for ESG performance and risk.

Second, this paper adds to the growing literature that parses the vast space of characteristics with seemingly option pricing-relevant information. Bali, Beckmeyer, Moerke, and Weigert (2023) apply machine learning techniques to predict option returns. Goyal and Saretto (2024) apply instrumented principal component analysis (IPCA) to study the latent factor structure of option returns and identify the difference between option implied and realized volatility of the underlying stock as the key factor capturing commonality in many option return predictors. Horenstein et al. (2024) compare the pricing performance of a latent, principal component-based factor model to a low-dimensional one. Käfer, Moerke, and Wiest (2025) apply the Bayesian model averaging approach proposed by Bryzgalova, Huang, and Julliard (2023) to study the structure of the SDF in the options market. My analysis is also applicable to an extensive set of option strategies. While not assessing the risks and factor structure underlying option returns at their fundamental level, relating option strategies to a substantial exposure to options on pharmaceuticals provides a straightforward way to analyze and understand the highly significant returns of numerous option strategies.

Third, this paper is part of a broader literature that critically reflects empirical approaches in options research. Notably, Duarte, Jones, and Wang (2024) demonstrate that the robustness of the variance risk premium in single-name equity options is sensitive to microstructure biases. O'Donovan and Yu (2024) assess the feasibility of option anomalies after transaction costs. Duarte, Jones, Mo, and Khorram (2024) document that most of the options return anomalies in Zhan et al. (2022) and the option illiquidity premium in Christoffersen, Goyenko, Jacobs, and Karoui (2018) are not profitable (before transaction costs) after correcting for look-ahead biases in the sample construction. While my paper does not point to technical errors in constructing option anomalies and foregoes the issue of implementability after trading costs, the exposure to pharmaceutical options in many option strategies should lead to many option anomalies being evaluated more skeptically. Empirical options researchers should more carefully draw inferences regarding the underlying risks and return drivers of option anomalies and consider the implications when options on pharmaceuticals largely contribute to abnormal returns.

## 2. Data

### 2.1. Data sources

I obtain price and characteristics data on US single-name options from OptionMetrics Ivy DB US. The sample period is from January 1996 to December 2022. Underlying stock prices and returns are from CRSP. Underlying stock characteristics are from Jensen et al. (2023) and Chen and Zimmermann (2022).[3] The daily risk-free rate (one-month US treasury rates) is from Kenneth French's online data library. Monthly risk-free rates are from OptionMetrics. The industry classification of underlying stocks into 49 industry groups follows Fama and French (1997) with the addition of the computer software industry.[4]

### 2.2. Data filters

I use option observations on underlyings that are common stocks trading on the NYSE, AMEX, or NASDAQ stock exchanges. Additionally, I do not keep option observations if the underlying stock's price is below \$5. I focus on at-the-money *call* options with the shortest maturity among options with more than one month until expiration. A large part of the literature studies these contracts due to their high trading volume (see, e.g., Horenstein et al., 2024; Zhan et al., 2022). Moreover, calls tend to be more liquid than puts. Generally, any predictive relation and factor structure established for call options is expected to be similar for puts due to the put-call parity. I adopt common approaches from the literature to arrive at my final sample of options (Bali et al., 2023; Käfer, Moerke, & Wiest, 2025; Zhan et al., 2022). Crucially, I apply all filters to a call-put pair based only on information available at the position initiation to avoid any forward-looking biases in the options sample (Duarte, Jones, Mo, & Khorram, 2024). In particular, at the end of the month $t$ and for each underlying, I select the closest to at-the-money call and put with expiration in month $t+2$ (average time to maturity: 50 days). The strike-to-spot ratio ($K/S$) must be between 0.8 and 1.2. Furthermore, the sample is limited to options with a standard expiration date on the third Friday of each month. I discard options without an implied volatility estimate by OptionMetrics. Moreover, I drop options on stocks with a scheduled dividend payment throughout month $t+1$ (the investment period for month-end to month-end option returns). I also exclude options for which the bid price is zero,

[3] The data, replication code, and documentation are available at https://jkpfactors.com/factor-returns and https://www.openassetpricing.com/.

[4] Available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

the ask is equal to or less than the bid, the mid price is below \$0.125, or the proportional bid-ask spread is above 50%. If options violate American option bounds, the observations are also discarded. To ensure the liquidity of options in the sample and to avoid stale quotes, I disregard contracts with zero open interest over the previous week. As most options at the end of each month have the same maturity, I drop observations with different expiration dates from most other options selected on that day. Finally, I keep only stock-level observations that have at least one call and one put option available after filtering.

### 2.3. Option returns

There are two established definitions of option returns in the literature: returns to writing a delta-neutral call and daily delta-hedged option returns. The excess return to writing a delta-neutral call from time $t$ to $t+1$ is defined as

$$\mathscr{R}(t, t+1) = \frac{\Delta_t S_{t+1} - C_{t+1}}{\Delta_t S_t - C_t} - 1 - r_{f,t}, \tag{1}$$

where $C_t$ is the midpoint of a call's bid and ask price, $S_t$ is the price of the underlying stock, and $\Delta_{C,t}$ is the Black-Scholes (1973) delta as provided by OptionMetrics. $r_{f,t}$ is the risk-free rate. $\mathscr{R}$ are the returns of an option writer who sells a call and buys the hedge position $\Delta_{C,t} S_t$ at time $t$, while keeping the hedge constant over the holding period until $t+1$. Since the stock position is not adjusted over the holding period, it constitutes a simple *initial* hedge. Further, it is conceptually similar to a conventional trading strategy that requires a cash outflow at position initiation (as $\Delta_{C,t} S_t - C_t > 0$ under no-arbitrage conditions).

The alternative return definition is based on a daily delta-hedging schedule. It is based on discreetly delta-hedged option gains, originally proposed by Bakshi and Kapadia (2003). Daily hedging comes closest to a delta-neutral strategy under continuous trading. For $N-1$ daily rebalance dates over the interval $T = \{t = t_0 < \ldots < t_N = t + \tau\}$, the delta-hedged call gain is defined as

$$\Pi(t, t+\tau) = C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta_{t_n} \left[ S(t_{n+1}) - S(t_n) \right] - \sum_{n=0}^{N-1} \frac{a_n r_n}{365} \left[ C_t - \Delta_{t_n} S(t_n) \right], \tag{2}$$

where $r_n$ is the risk-free rate at $t_n$ and $a_n$ is the number of calendar days between rehedging dates $t_n$ and $t_{n+1}$, and is set equal to 1. In contrast to the return on writing a delta-neutral call $\mathscr{R}$, Equation (2) is the value of a zero-cost portfolio consisting of a long option contract and a (daily) rebalanced hedge position in the underlying, where the net cash position earns the risk-free rate. I follow Cao and Han (2013) in scaling the call gain by the securities' value at position initialization, namely $\Delta_t S_t - C_t$. Moreover, analogous to Equation (1), I consider the negative of $\Pi(t, t+\tau)$ in the nominator, which yields the daily delta-hedged return from the perspective of a call writer,

$$\frac{-\Pi(t, t+\tau)}{\Delta_t S_t - C_t}. \tag{3}$$

Daily delta-hedged option returns are widely established in the literature on cross-sectional option return predictability and option anomalies (Bali et al., 2023; Horenstein et al., 2024; Käfer, Moerke, & Wiest, 2025, among others). Tian and Wu (2023) show that a major advantage of this return specification is the removal of about 90% of the directional risks embedded in the option position related to the underlying stock (relative to a naked option investment). In contrast, initial delta-hedging reduces the exposure by 70%. This effect typically results in a lower return variability of daily-delta hedged returns, especially when the option contract moves deeply in or out of the money over its holding period.

### 2.4. Descriptive statistics and mean option returns by industry

Table 1 summarizes pooled descriptive statistics of option returns and key option-level characteristics. For both initial and daily hedging schedules, returns to delta-neutral call writing are positive on average, in line with option writers being compensated for carrying inherent volatility risk (Bakshi & Kapadia, 2003; Coval & Shumway, 2001). As highlighted by Tian and Wu (2023), initial delta-hedged returns are higher for initially delta-hedged calls and considerably more volatile than their daily delta-hedged counterpart.

Considering average option returns by industry produces the introductory Figure 1. I use the Fama-French 49 (FF49) industry group classifications and only focus on industries with sufficient firm coverage. To do so, I depict only industries with at least 30 firm observations per month in more than 50% of the sample months (162 of a total of 323 months). Figure 1 then depicts the average monthly option returns of 15 industries. The stars above the return columns denote significance levels based on Newey and West (1987) standard errors. The pharmaceutical industry ("13 - Drugs", SIC codes: 2830-2836) emerges as the industry with the highest average option returns by far, with 1.25% and 1.11% monthly returns for initial and delta-hedged returns. The only other industry with highly significant option returns for both return specifications is group 12, "Medical Equipment". For at least one specification, all other major industry groups do not display call returns that are significantly different from zero, highlighting that significantly positive average returns on delta-neutral call writing are present in only a select few industries.

## 3. Baseline long-short option portfolios

### 3.1. Sorting characteristics

To assess the impact of industry exposure on options strategies, I construct call option portfolios based on underlying stock-level characteristics. I initially focus on the ten option anomalies proposed in Zhan et al. (2022) (henceforth ZHCT). These variables are featured in related work in empirical option research such as Duarte, Jones, Mo, and Khorram (2024), Horenstein et al. (2024), and O'Donovan and Yu (2024) and provide a helpful starting point for assessing the presence of return predictability in the cross-section of option returns. The anomalies are based on the following stock characteristics:

1. *Cash-to-assets ratio* (CH) is the value of a firm's cash holdings over the value of the firm's total assets (Palazzo, 2012).
2. *Cash flow variance* (CFV) is the monthly ratio of cash flow to market capitalization over the last 60 months (Haugen & Baker, 1996).
3. *Analyst earnings forecast dispersion* (DISP) is the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecasts (Diether, Malloy, & Scherbina, 2002).
4. *One-year new share issues* (ISSUE_1Y) is the one-year growth of the underlying stock's shares outstanding (Pontiff & Woodgate, 2008).
5. *Five-year new share issues* (ISSUE_5Y) is the five-year growth of the underlying stock's shares outstanding (Daniel & Titman, 2006).
6. *Total external financing* (TEF) is the net share and net debt issuance, scaled by the firm´s total assets (Bradshaw, Richardson, & Sloan, 2006).
7. *Profit margin* (PM) is defined as EBIT over total sales (Soliman, 2008).
8. *Stock price* (PRICE) is the underlying stock's close price at the end of the previous month.
9. *Operating profitability* (PROFIT) is defined as EBITDA minus interest expenses over book equity (Fama & French, 2015).

10. *Altman Z-score* (ZS) is defined as in (Dichev, 1998), with higher ZS values indicating a lower probability of bankruptcy.

I provide detailed information on the construction of characteristics in Internet Appendix B.1. Henceforth, I will refer to these sorting characteristics and the corresponding long-short portfolios as option *anomalies*. I use the term anomaly because the abovementioned characteristics are not self-evidently linked to known risks in the options market.

I also consider several sorting variables that constitute *risk factors* in the option returns space. Namely, I use the underlying stock's Amihud (2002) *illiquidity* measure (AMIHUD) and the stock's *idiosyncratic volatility* (IVOL) based on daily Fama-French (1993) resiudals over the previous month. ZHCT demonstrate that these two factors perform well in explaining the returns of the ZHCT anomalies. The AMIHUD and IVOL factors capture market maker hedging costs related to the illiquidity (Kanne et al., 2023) and the difficulty of hedging options with high idiosyncratic volatility (Cao & Han, 2013). Moreover, Cao and Han (2013) explain that IVOL might further capture higher demand for options on stocks with high idiosyncratic volatility, leading to overvaluation of these option contracts. In addition, I include the five risk factors introduced by Tian and Wu (2023) (henceforth TW), with the first three being linked to risks of market making and the other two representing more general risks of writing options:

1. *Delta-hedging cost* (HC) is defined as $\mathrm{HC}_t = \sigma_t \sqrt{(1-\rho_{t,M}^2)/\mathrm{DV}_t}$, where $\sigma_t$ denotes the stock's historical return volatility estimator, $\rho_{t,M}$ the return correlation of the stock with the aggregate market portfolio, and $\mathrm{DV}_{t,i}$ denotes the average dollar trading volume (in thousands) of the stock. Options are more costly to hedge if the underlying is more volatile, not strongly correlated with the market portfolio (inhibiting hedging via a broad index instrument), and illiquid.
2. *Volatility risk* (VR) is the standard deviation of daily changes of stock $i$'s implied volatility over the past month. VR constitutes the risk of stochastic volatility that cannot be entirely removed through delta-hedging.
3. *Jump risk* (JR) is defined as the product of the underlying stock's excess kurtosis and historical return volatility over the previous month. JR reflects the difficulty of mitigating the risk of large price movements (in contrast to small, diffusive price changes) through delta hedging.
4. *Volatility risk premium* (VRP) is defined as the difference between the stock's one-month

implied volatility and historical volatility estimated with daily stock returns over the previous 12 months (Goyal & Saretto, 2009). VRP is an *ex-ante* measure of the volatility risk premium reflecting the market's price of volatility relative to a historical estimate. It also captures general over- or underpricing of volatility inherent in option prices.

5. *Historical risk premium* (HRP) defined as the average return on the stock's at-the-money options over the past 12 months, excluding the most recent. HRP reflects option momentum effects, as in Heston et al. (2023), which may be driven by persistence in the relative magnitude of unspecified risk sources that drive option returns.

Details on constructing option risk factors are provided in Internet Appendix B.2.

### 3.2. Overview of long-short portfolio returns

I follow ZHCT in constructing month-end, equal-weighted decile portfolios of the above anomaly and factor characteristics. I then compute the 10-minus-1 portfolio return as an anomaly or factor return. A minus sign preceding a characteristic's name indicates that options are sorted inversely based on the respective characteristic. I report the average time-series return of option anomalies and factors in Table 2. I depict $t$-stats based on autocorrelation and heteroskedasticity adjusted Newey and West (1987) standard errors in parentheses.

Several key observations emerge. First, the long-short returns using a mere initial delta-hedge tend to be more volatile than their daily delta-hedged counterpart. This effect produces less significant average returns, especially for anomaly characteristics such as CH and -PM. In addition, it highlights the benefit of using a daily delta-hedging schedule as noted by TW, which considerably reduces directional exposure and return variation in option returns, resulting in more stable long-short returns. Especially for the ZHCT anomalies, the individual delta-edged returns display weaker statistical significance and are sometimes even insignificant (e.g., DISP and -ZS). This insight aligns with the results in Duarte, Jones, Mo, and Khorram (2024), who document that most initially delta-hedged anomalies turn insignificant after controlling for forward-looking filters in ZHCT. In my sample construction, I also ensure that I do not use forward-looking information. The main reason why many initially delta-hedged ZHCT anomalies are statistically significant in Table 2 appears to be the longer sample period until 2022. In line with Jones, Wang, and Zhang (2024), the profitability of option anomalies has increased since 2016 (the end of the sample in ZHCT) and especially after the outbreak of the COVID-19 pandemic. Using the same sample period as in ZHCT (January 1996 until

April 2016), I obtain qualitatively similar mean returns as in Duarte, Jones, Mo, and Khorram (2024), which are far below the original infeasible ZHCT results (see Table A1 in the Internet Appendix).[5]

Due to the overall weaker anomaly performance of initially delta-hedged returns and to enhance the readability and structure of subsequent exhibits, I focus on daily delta-hedged returns going forward. Nevertheless, I briefly comment on the validity of my findings for initially hedged returns throughout the remainder of this paper and provide selected tabulated results in the Internet Appendix.

### 3.3. Risk adjustments

An important empirical question is whether the ZHCT anomalies generate alpha over option factors linked to risks in the options market. I run the following regression separately for each of the ten ZHCT anomalies $j$:

$$Anomaly_{j,t} = \alpha_j + RiskFactor_t^\top \beta_j + \varepsilon_{j,t}, \tag{4}$$

where $RiskFactor_t$ is a vector of option risk factors. I consider factor models based on the models proposed by ZHCT themselves and TW separately. I also combine the two proposed models by adding the IVOL factor to the TW model (TW+ZHCT). I do not add AMIHUD to the TW factors, as this factor is highly correlated ($\rho > 0.9$) with the hedging costs (HC) factor, which is also based on a stock liquidity measure (underlying stock trading volume).[6]

Table 3 summarizes the alpha coefficients from Equation (4). Crucially, and especially after controlling for both ZHCT and TW factors, most anomalies turn insignificant or even negative. This result highlights that many anomalies in ZHCT ultimately stem from risks such as hedging costs, jump risk, or volatility risk. In that sense, most of these anomalies are not abnormal as they appear to be explained by risks peculiar to the options market and its market-making structure. A notable exception appears to be the cash-to-assets anomaly, CH. The risk adjustments noticeably impact CH, mostly when adjusting for the combined TW+ZHCT model, where its $t$-stat drops below 3. However, CH remains the only anomaly with a significantly positive alpha above 2 throughout all specifications and consistently exhibits

[5] The summary statistics of initially delta-hedged returns (the first line in Table 1 are also very close to the bias-free sample in Duarte, Jones, Mo, and Khorram (2024).

[6] I choose to include HC over AMIHUD as it is the much “stronger” risk factor in terms of mean return in Table 2. In unreported tests, the key takeaways remain consistent when using AMIHUD instead.

the highest positive alpha point estimate.

The exceptionalism of the CH anomaly among simple, stock-based sorting variables has been noted in previous work. Notably, O'Donovan and Yu (2024) document that it is among the few stock-based characteristics that remain profitable after transaction costs, after applying mild cost mitigation strategies. In addition, Horenstein et al. (2024) shows that including CH considerably improves the pricing performance of low-dimension option factor models when explaining the returns of more than 100 option long-short portfolios. This insight indicates that CH might carry strong explanatory power for the cross-section of option returns across various sorting characteristics. In the following, Section 4 outlines that the strong performance of CH essentially boils down to the high cash holdings of pharmaceutical firms, which can be generalized to other prominent characteristics typical of the pharmaceutical industry.

## 4. Industry exposure and option anomaly returns

### 4.1. Industry exposure in baseline long-short portfolios

From the perspective of option writers, option anomalies yield significantly positive returns and are not fully explained by option risk factors in the case of CH. At the same time, the pharmaceutical industry stands out as the options on these stocks provide by far the highest delta-neutral returns on average. These facts prompt a natural inquiry into whether the profitability of option strategies arises from an "industry bet" on pharmaceutical stocks.

I compare the long and short legs of option anomalies and factors regarding their exposure to specific industries. Figure 2 visualizes the average monthly difference between the share of a given industry in a characteristic's long leg and its short leg. For instance, a value of 0.2 in a cell indicates a 20 percentage point difference between the share of industry $i$ in characteristic $j$'s decile 10 and its share in decile 1. Dark (light) color in the heatmap indicates a positive (negative) difference in industry shares. Furthermore, to avoid unnecessary clutter, I only show the numeric values for differences with an absolute value greater than 0.1. Finally, showing the difference between industry shares in the long and short legs avoids an unfair advantage for larger industry groups, which would, by construction, display a larger share in a single leg, even if individual firms were distributed equally across all ten deciles. This consideration is essential for my purpose, as the pharmaceutical industry is one of the largest in terms of the average number of firms per month in the options sample: On average, there are 103 options on pharmaceuticals per monthly cross-section of option observations; 8.5% of the average total number of options per month (1,217).

Figure 2 reveals that most industries do not tend to be overweight in an anomaly's or factor's long leg relative to its short leg. The only major exception is the pharmaceutical industry, with pharmaceutical firms accounting for a significantly larger share in the long leg for a handful of sorting characteristics. Namely, CH (0.42) and the profitability-related variables, -PROFIT (0.38) and -PM (0.31), display a share of pharmaceutical firms in their top decile that is more than 30 percentage points higher than in their bottom decile. Furthermore, the variables related to external financing and share issuance, TEF, ISSUE_1Y, and ISSUE_5Y have a higher share of pharmaceuticals in decile 10 of more than 15 percentage points. Interestingly, a moderate long bias (0.11 to 0.16) in pharmaceuticals also affects the option risk factors IVOL, HC, VR, and HRP, indicating that options on pharmaceuticals are subject to these risks or are at least associated with higher values of the characteristics proxying for these risks.

In summary, sorting options on select underlying stock characteristics leads to a relative overweight of pharmaceutical stocks in the strategy's long leg. Given these stocks' high option returns, this insight can enhance understanding of these option strategies. In this context, it is worth noting that, in fact, the long leg drives the profitability of options strategies. Table A2 shows individual decile sort returns and demonstrates that it is the strong positive performance of decile 10 (with no clear monotonic increase over the preceding lower deciles) rather than a pronounced negative performance of decile 1 that is responsible for the profitability of the long-short anomalies. This observation further suggests that industry concentration in the long decile 10 might contribute to option anomaly returns.

### 4.2. Adjusting for a pharmaceutical option factor

Given the excessive exposure to pharmaceutical firms in some option strategies, I investigate how controlling for this exposure can explain the ZHCT anomaly returns. To do so, I construct a simple long-short pharmaceutical "factor", $f^{\text{PHARMA}}$, that is long in all options on pharmaceutical stocks and short in all other option contracts.[7] In Table 4, the mean return on $f^{\text{PHARMA}}$ is 1.13% per month ($t$: 10.63). Controlling $f^{\text{PHARMA}}$ for the ZHCT and TW risk factors yields a statistically significant alpha of 0.46% ($t$: 3.34). The pharmaceutical option

[7] The pharmaceutical factor that I construct differs from the one employed by Wang (2024) who uses a long-only factor to validate an option strategy based on Large Language Models predictions. I find that a long-short pharmaceutical factor is superior in my pricing tests when pricing long-short anomalies.

factor loads moderately positively on idiosyncratic volatility and heavily on the historical risk premium (HRP) that captures momentum effects in the options market. The strong loading on HRP indicates that options on pharmaceuticals display return continuation with persistently positive returns. Hence, $f^{\text{PHARMA}}$ is not unambiguously driven by market-making risks like HC, VR, and JR, but rather by option return persistency linked to other unspecified sources of risk or mispricing, leading to options on pharmaceuticals consistently outperforming. In my analyses, I assign equal weights to individual options when constructing long-short strategies, a standard in the literature on option return predictability (Goyal & Saretto, 2024; Horenstein et al., 2024; Zhan et al., 2022). Following Käfer, Moerke, and Wiest (2025), in columns 3 to 6 in Table 4, I also report results for weighting options by dollar open interest at portfolio formation and for excluding illiquid options with proportional bid-ask spreads above the monthly median. These alternatives put more emphasis on liquid options with lower transaction costs; however, $f^{\text{PHARMA}}$ means and alphas are not (if at all) far below the equal weighting setting.

The first column of Table 5 depicts the baseline raw long-short anomaly return from Table 2 for daily hedged returns. The second column reports the regression alpha after regressing option strategy returns on $f^{\text{PHARMA}}$. Most notably, the average CH anomaly return turns insignificant ($t$: 7.17 vs. 0.47), indicating that the exposure to the pharmaceutical industry drives the anomaly. Other anomalies affected by a long bias in pharmaceutical stocks, such as operating profitability (-PROFIT) and total external financing (TEF), also become insignificant. The profit margin (-PM) anomaly is also characterized by an overweight in pharmaceuticals in its long leg and remains statistically significant. However, its alpha reduces to less than one-third compared to the baseline mean return.

I further control for *industry-adjusted* option risk factors in columns 3 and 4 of Table 5, denoted with a "*" superscript compared to the unadjusted factors. I sort options based on monthly industry-demeaned characteristics to obtain industry-adjusted factors. The purpose of this procedure is not to enhance the performance of these factors, as in stock factor papers like Novy-Marx (2013). Rather, as Figure 2 suggests, risk factors may also be exposed to a slight bias in pharmaceuticals. I aim to avoid conflating these factors with the $f^{\text{PHARMA}}$ factor and assess their pricing performance independently of cross-industry effects. Moreover, adding industry-adjusted factors to $f^{\text{PHARMA}}$ in multivariate regressions accentuates the impact of pharmaceutical options in explaining option anomalies.

Recall that, except for CH, all other ZHCT anomalies turned insignificant after controlling for the baseline, industry-*unadjusted* TW+ZHCT model specification. Yet, in column 3, the factors with notable pharmaceutical exposure in Figure 2 (ISSUE_1Y, ISSUE_5Y, TEG, -PM, -PROFIT, and CH) remain significantly positive after controlling for TW*+ZHCT*, showing that accounting for return differences across industries reduces the explanatory power of the risk factors. This effect is especially pronounced for CH, which remains significantly with a $t$-stat of 5.70, far above all other strategies. Finally, when jointly controlling for $f^{\text{PHARMA}}$ and the TW*+ZHCT* factors in column 4 of Table 5, all but one anomaly becomes insignificant with a $t$-statistic below 2. This result indicates that ZHCT anomaly returns are fully captured by exposure to the pharmaceutical sector and risk factors adjusted for the industry tilt of the factors. The exception remains the anomaly sorting on the underlying stock price (-PRICE). Yet, the significance ($t$: 2.08) is modest, and -PRICE is also not fully explained by the industry-unadjusted TW and ZHCT factors in Table 3.

The main conclusion of this subsection is that exposure to the pharmaceutical sector accounts for a significant portion of the profitability of select option anomalies, such as the CH anomaly. I control for a long-short pharma factor, $f^{\text{PHARMA}}$, to demonstrate that exposure to this particular industry explains the pattern in the cross-section of returns. $f^{\text{PHARMA}}$'s significant alpha over option risk factors and its ability to explain the CH return more successfully than the TW and ZHCT risk factors in Table 3 points toward additional pricing-relevant information underlying the pharmaceutical option factor. As an alternative to mitigate the impact of implicit "sector bets" in option strategies, Table A3 displays qualitatively similar results when excluding options on pharmaceutical stocks in constructing option anomalies.[8] Tables A4 and A5 provide qualitatively similar results when performing the same analysis as in Table 5 for put options and initially hedged calls.

### 4.3. Pharmaceutical firms, cash holdings, and growth opportunities

In this section, I outline and revisit the connection between the pharmaceutical industry and the sorting characteristics of option strategies largely explained by $f^{\text{PHARMA}}$. A natural starting point is the corporate cash holding variable, which relates to the most persistent op-

[8]Another, less obvious way to mitigate the impact of the pharmaceutical industry on option strategies is to weight individual options in portfolios by the market capitalization of the underlying stock. The mechanisms and economics of pharmaceutical stocks and options in the subsequent analyses are accentuated for smaller pharmaceutical firms. However, this weighting scheme does not necessarily reflect the true composition of the equity options market and more strongly contrasts with the standard in empirical options research that relies on an equal-weighting scheme.

tion anomaly relative to option risk factors, while being fully subsumed by the pharmaceutical factor. Figure 3 plots the monthly average of the cash-to-assets ratio of the NYSE, AMEX, and NASDAQ common stock universe since 1960. As shown by Bates et al. (2009) and Graham and Leary (2018), the cash holdings of individual firms have increased considerably since the 1980s. This increase is far more pronounced for pharmaceutical stocks, with an average CH value of 60% by 2020 compared to roughly 20% in other sectors. This stylized fact aligns with the findings by Graham and Leary (2018), who document that high cash holdings are concentrated among firms in the technology and healthcare sectors, the latter including pharmaceuticals. Crucially, firms with strong growth opportunities tend to hold more cash reserves, as examined by Opler et al. (1999): Limited outside funding can prevent these firms from investing in profitable projects, leading to precautionary cash holdings. Begenau and Palazzo (2021) and Falato et al. (2022) come to the analogous conclusion of elevated cash holdings being concentrated among R&D-intensive firms and firms that heavily invest in intangible capital. Pharmaceutical firms engage in intensive R&D activities, and especially for smaller firms, their corporate success and future profits often hinge on the successful development of a new drug, making pharmaceuticals the epitome of firms with high growth potential. Further, Schroth and Szalay (2007) show that high cash holdings in the pharmaceutical sector allow firms to invest and innovate faster than competitors. Finally, Denis and McKeon (2018) and Begenau and Palazzo (2021) highlight that higher intangible investments lead to operating losses and stronger dependence on the precautionary liquidity reserve of corporate cash. This insight explains why, next to CH, the (inverse) profitability-characteristics -PM and -PROFIT display a high concentration of pharmaceuticals in their long leg.

The relation between cash holdings, growth opportunities, and pharmaceuticals links my findings to the work by Andreou et al. (2024). The authors show that options on firms with high growth potential are overvalued, leading to positive returns from the perspective of an option writer. I use sorting characteristics related to firm growth potential to demonstrate that options strategies based on these sorting variables are largely, if not even fully, due to options in the pharmaceutical sector. In particular, I consider the growth option variable (GO) from Andreou et al. (2024), defined as the percentage of a firm's market capitalization arising from future-oriented growth opportunities. I further consider the cash-flow-to-price ratio (CFP), market-to-book value of assets (MABA), R&D to assets (RD_AT), and R&D intensity (RD_SALES). These characteristics are alternative growth opportunity measures as high-growth-potential firms typically receive low cash flows, display higher market valuations, and invest heavily in R&D. Details on the definitions and construction of these variables are outlined in Internet Appendix B.3.

I start by comparing the monthly averages of the mean characteristic values for pharmaceuticals and other sectors in Panel A of Table 6. All variables are winsorized each month at the 0.5% and 99.5% levels to mitigate the impact of outliers. As expected, pharmaceuticals exhibit significantly higher growth opportunities, asset valuation, and R&D investments, and receive a significantly lower cash flow. The last column of Panel A shows the average difference in the share of pharmaceutical firms between deciles 10 and 1, analogous to the heatmap in Figure 2. The differences are large with values above 20 percentage points and even more pronounced for RD_AT and RD_SALE compared to CH (59% and 70% versus 42%). I construct option strategies in Panel B of Table 6 by sorting on the five growth-related characteristics. Unsurprisingly, and except for MABA, the long-short portfolios yield highly significant and positive returns. After controlling for $f^{\text{PHARMA}}$, all $t$-stats fall below 2. This reduction in alpha relative to the strategies' mean returns is much stronger than when controlling for the industry-demeaned TW and ZHCT risk factors in column 3. The alphas for jointly controlling for TW*+TW* and $f^{\text{PHARMA}}$ are similar to when only controlling for $f^{\text{PHARMA}}$. Finally, I also show alphas when controlling for the full, not-demeaned risk factors in column 5. Like CH in Table 3, not all anomalies are fully explained by the standard risk factors. In particular, RD_AT and RD_SALE remain at monthly alphas above 0.4% and $t$-stats of 2.40 and 3.21, respectively.

The key takeaways from this subsection's analysis are twofold. First, as apparent from column 5 in Panel B of Table 6, established risk factors in the options market do not fully price options on pharmaceuticals or strategies with excessive long exposure to these options. Second, I confirm the results of Andreou et al. (2024) and show that options strategies based on growth option characteristics are driven mainly by stocks in the pharmaceutical sector alone, indicating a strong cross-industry rather than within-industry effect that drives these strategies.

### 4.4. Generalization to the option anomaly zoo

To extend my findings to an extensive set of option anomalies in the spirit of Horenstein et al. (2024), I select arbitrary stock-level characteristics to sort options into long-short decile portfolios analogous to my baseline setting in Section 3. I use the characteristics provided by Jensen et al. (2023) that constitute factors in the stock market. I exclude characteristics if they are duplicates of ZHCT or other sorting variables used throughout this paper. The final list of 140 characteristics is in Internet Appendix C.1.

As these characteristics represent risk factors in pricing stocks, there is no trivial reason why they should lead to abnormal profits of delta-neutral investments. Nevertheless, as depicted in Panel A of Table 7, which summarizes average strategy returns and alphas, sorting by arbitrary stock characteristics yields considerable option returns, with 48% of the long-short portfolios exhibiting an absolute $t$-stat greater than 3.[9] I follow Horenstein et al. (2024) and Harvey, Liu, and Zhu (2016) in considering the stricter $t$-stat hurdle of 3. I also show the average strategy return or alpha, the average absolute $t$-stat, and adjusted $R^2$ when regressing strategies on option factors. My results align with those of Goyal and Saretto (2024) or Horenstein et al. (2024), who also document a large "zoo" of seemingly abnormal option returns based on various sorting characteristics. Notably, controlling for the pharmaceutical option factor (Alpha $f^{\text{PHARMA}}$) reduces the share of significant anomalies with $|t| > 3$ to 23%. This reduction in highly significant anomalies is similar in scale to controlling for industry-demeaned risk factors, TW*+ZHCT*. Jointly controlling for $f^{\text{PHARMA}}$ and TW*+ZHCT* eliminates almost all significant anomalies with only 3% of factors displaying absolute $t$-stats above 3. Crucially, controlling for the full, industry-*unadjusted* TW and ZHCT risk factors yields a slightly worse pricing performance with a share of $|t| > 3$ of 8%. Hence, established option risk factors are already effective in explaining abnormal option returns. However, it is critical to point out that for some characteristics similar to CH and the R&D expenditure variables in Table 6, a heavy concentration of pharmaceuticals in a strategy's long leg can lead to risk factors not fully explaining strategy returns. Hence, specifically emphasizing the exposure to pharmaceutical options through $f^{\text{PHARMA}}$ is beneficial when pricing option strategies.

Panels B and C of Table 7 summarize subsamples of option anomalies based on their inherent bias towards options on pharmaceuticals. Analogous to Figure 2, I determine the bias towards pharmaceuticals by comparing the share of pharmaceutical stocks between decile 10 and decile 1. By construction, $f^{\text{PHARMA}}$ is more effective in reducing abnormal portfolio returns in Panel B with high bias. Nevertheless, the difference in profitability magnitude and significance reduction is remarkable. In Panel B, the 50 portfolios with the highest exposure to pharmaceuticals (average absolute decile 10-1 difference: 23%) are characterized by highly

[9] In Internet Appendix C.2, I provide the mean returns and alphas of the individual option strategies that underlie Table 7.

significant returns with an average $|t|$ of 5.83 and a share of $|t|$ above 3 of 84%. Merely controlling for $f^{\text{PHARMA}}$ reduces this share to 26%, and only one strategy remains significant after adding industry-demeaned risk factors. On the other hand, the 50 low-exposure portfolios in Panel C (average absolute decile 10-1 difference: 1.6%) display far weaker average returns and tend to be better explained by option risk factors.

Figure 4 displays the reduction in the percentage of anomalies with an absolute alpha $t$-stat larger than 3 grouped by the stock factor clusters in Jensen et al. (2023). I show the impact of regressing anomaly returns only on $f^{\text{PHARMA}}$ and exclude clusters with fewer than five observations. Clusters with significant anomaly returns tend to be reduced considerably by only controlling for the pharmaceuticals factor. In particular, the *Profitability* and *Value* clusters are heavily affected due to the low profitability and high market valuation of pharmaceuticals. In addition, the option anomaly returns in the *Low Leverage* cluster also exhibit a larger impact of $f^{\text{PHARMA}}$. This cluster sorts by characteristics such as firm age and asset tangibility, relating them to pharmaceuticals, which are frequently young firms with a high proportion of intangible assets. Finally, exposure to pharmaceuticals does not impact the significance of anomalies in clusters such as *Investment*, *Low Risk*, and *Seasonality*, due to the weaker link between the underlying characteristics and pharmaceutical stocks.

The main conclusion from generalizing my results to a large set of option strategies is twofold. First, controlling for anomaly return in univariate regressions reduces the number of highly significant strategies for $f^{\text{PHARMA}}$ by roughly half. Although this effect might be driven by the exposure of options on pharmaceuticals to various risk factors (particularly HRP, see Table 4), it is noteworthy that the profitability of many options strategies largely boils down to their exposure to pharmaceutical options. Second, adding $f^{\text{PHARMA}}$ to the factors proposed by ZHCT and TW incrementally improves the pricing performance of an option factor model. This insight highlights that common risk factors do not fully capture the premium inherent in pharmaceutical options. In particular, a handful of highly significant strategies that originate from a stark long bias in pharmaceuticals see their alpha reduced after accounting for $f^{\text{PHARMA}}$ in the TW+ZHCT model as well. The stark and persistent performance of these strategies and $f^{\text{PHARMA}}$ itself provides an explanation why CH, an anomaly driven by options on pharmaceuticals, characterizes the factor structure of equity option returns in Horenstein et al. (2024).

## 5. Properties of options on pharmaceuticals

A main result of the previous section is that controlling for exposure to the pharmaceutical sector is beneficial when explaining option strategies. As established option risk factors do not fully account for the performance of options on pharmaceuticals, the final section of this paper addresses additional properties of pharmaceutical stocks and their options that might explain their strong returns.

### 5.1. Option demand

I begin by considering the effects of option demand on pharmaceuticals, which might impact the option prices. As demonstrated by Andreou et al. (2024), high demand by option end-users for options on firms with high growth potential leads to higher prices of these contracts and subsequently higher returns of option writers selling these contracts. I examine three basic proxies for option demand pressure proposed by Cao and Han (2013): Option open interest (OI) scaled by the volume in the underlying stock over the previous month, OI scaled by shares outstanding, and option volume (OVOL) over stock volume over the previous month. As is common in the literature, I consider the open interest and volume of all (call) contracts on a stock. Option demand pressure has a larger impact on prices if dealer positions are imbalanced, making delta-hedging more expensive (Bollen & Whaley, 2004; Garleanu et al., 2009). To account for the net demand of non-dealer market participants, I use signed volume data from May 2005 until November 2020 from the NASDAQ International Securities Exchange (ISE) Trade Profile. I recursively compute the (unscaled) net open interest as in Goyenko and Zhang (2021) and Ni, Pearson, Poteshman, and White (2021), aggregated for all nonmarket maker trader types (customer, professional customer, and firm trades), as

$$
\begin{aligned}
OpenInterest^{Buy}_{i,j,t} &= OpenInterest^{Buy}_{i,j,t-1} + Volume^{OpenBuy}_{i,j,t} - Volume^{CloseSell}_{i,j,t} \\
OpenInterest^{Sell}_{i,j,t} &= OpenInterest^{Sell}_{i,j,t-1} + Volume^{OpenSell}_{i,j,t} - Volume^{CloseBuy}_{i,j,t} \\
\mathrm{NOI}_{i,j,t} &= OpenInterest^{Buy}_{i,j,t} - OpenInterest^{Sell}_{i,j,t}.
\end{aligned}
\tag{5}
$$

$Volume^{OpenBuy}$ and $Volume^{OpenSell}$ are volumes to establish new purchased and written call positions. $Volume^{CloseBuy}$ and $Volume^{CloseSell}$ are volumes to close existing written and purchased positions. Net open interest is then the difference between buy and sell open interest, which I further scale by the shares outstanding of the underlying stock following Lakonishok, Lee, Pearson, and Poteshman (2007). NOI is first computed at the call contract level $j$ and then aggregated to the stock level $i$.

I regress the option demand variables on an indicator variable, PHARMA, that is equal to 1 for underlying stocks in the pharmaceutical sector and 0 otherwise. I employ Fama-MacBeth (1973) cross-sectional regressions. I also control for a handful of controls that are typically associated with option demand. First, I control for the logarithm of the underlying stock's market capitalization (SIZE). I further control for IVOL and VR: As shown by Cao and Han (2013) and Cao et al. (2023), both idiosyncratic volatility and volatility uncertainty are associated with higher option demand. Lastly, I control for the VRP and firm growth potential (GO) as general proxies for option mispricing potentially related to demand pressure. Table 8 presents univariate and multivariate regression results. The coefficient on PHARMA is positive and significant in all eight specifications. The results are more pronounced for the unsigned OI and OVOL specifications in columns 1 to 6, indicating a generally increased trading activity and demand for pharmaceutical options. Yet, with $t$ stats slightly below 3, the results for net open interest indicate that option end-users exhibit demand for pharmaceutical options, leading to unbalanced demand for these options, for which option market makers require compensation.[10]

### 5.2. Drug development and jump surprises

Andreou et al. (2024) relate the demand for options on firms with high growth potential to the lottery-like behavior of these stocks, characterized by large positive price jumps. Large price jumps, especially related to news releases on the progress of drug development, such as clinical trials, patent filings, and FDA approvals (see, e.g., Cho, Singh, & Lo, 2024; Mc Namara & Baden-Fuller, 2007) are also typical features of pharmaceutical stocks. Given the long and expensive drug development process (DiMasi, Hansen, & Grabowski, 2003), news reflecting the viability of individual drugs leads to considerable price movements. To revisit the presence of stock price jumps in pharmaceutical stocks, I follow the approach in Andreou et al. (2024) to determine jump surprises in underlying stocks. I start by estimating daily stock price jumps following the approach by Kapadia and Zekhnini (2019). I use an exponentially weighted

[10] Horenstein et al. (2024) relate the importance of the CH in pricing option portfolios to cash holding being associated with reduced adverse selection problems and option liquidity as argued by Deng and Nguyen (2024). The increased option trading activity for high-cash firms might be related to trading in pharmaceutical options. However, while Deng and Nguyen (2024) account for industry fixed effects, my results suggest a strong cross-industry effect, with the relationship between cash and option liquidity appearing to be a correlation effect due to the characteristics of pharmaceuticals and not necessarily a causal link.

moving average (EWMA) model to estimate a stock's conditional volatility.[11] I then define a stock price jump as a return observation larger than three times the stock's conditional volatility on day $t$ in absolute terms.[12] To assess the magnitude of unexpected jump *surprises* instead of generally more volatile stocks, I follow Andreou et al. (2024) in subtracting a jump extrapolation measure (EXTRAP) estimated over the previous six months from jump returns on a jump day $t$. I construct the (positive) jump extrapolation measure as

$$\text{EXTRAP}_{i,t}^{posjump} = \frac{1}{\sum_{k=1}^{6} 1/k} \times \sum_{j=1}^{6} \left( \frac{1}{j} \times \text{PJUMPR}_{i,t-j} \right), \tag{6}$$

where PJUMPR is the (positive) jump return defined as the maximum of positive jumps during a previous month $t-j$. Negative jump extrapolation is defined analogously. In contrast to Andreou et al. (2024), I do not extrapolate the cumulative sum of jump returns in case of multiple jumps over a month, as I consider jump surprises on individual days instead of at the aggregate monthly level. Jump months can exhibit positive or negative jumps solely; otherwise, the observations are removed to distinguish between high volatility episodes and one-directional jumps.

To obtain an overview of firm-specific events that lead to jump surprises, I collect news data for jump days from January 2000 to October 2022 using RavenPack, a leading provider of news analytics that identifies news stories relevant to individual firms. I outline my detailed approach of filtering the RavenPack data to obtain meaningful, novel, and distinct news events in Internet Appendix D.1. I show pooled mean jump return surprises ($\bar{R}_{JS}$) of both pharmaceuticals and all other firms in Table 9, grouped by the news categories of headlines on jump days (RavenPack event taxonomy: "group"). N refers to the number of identified news events next to the share of total news by group on jump days. Turning first to news on positive jump days in Panel A, the first notable observation is that pharmaceuticals display stronger jump surprises than other sectors (13.8% vs. 10.3%). Most importantly, the news group exhibiting the highest average jump surprises for pharmaceuticals is "products-services" with an $\bar{R}_{JS}$ of 23.2% compared to 11.8% for non-pharmaceuticals. Typical news in this group is about product launches. In the case of pharmaceuticals, these events refer to updates on clinical trials, patents,

[11]The conditional volatility of for day $t$ is given as $\sigma_{i,t} = (1-\lambda)\sum_{s=1}^{t-1} \lambda^s r_{i,t-s}^2$, where $\lambda = 0.94$ following the RiskMetrics approach (Kapadia & Zekhnini, 2019).

[12]Following Andreou et al. (2024), I also use raw instead of idiosyncratic stock returns as they are likely to be more salient to investors, and jumps based on raw returns more directly impact the returns of delta-neutral positions.

or FDA approvals. Such events also make up for a considerably larger share of jump events for pharmaceuticals (14%) compared to other firms (4%). As a reference, Internet Appendix D.2 lists examples of news headlines by group on the days with the most extreme jump surprises. News groups indirectly related to the drug development process, such as "investor-relations" (which includes events like conference calls following clinical trials) and "partnerships" (e.g., a small and large firm collaborating on a drug development project), also display far higher average jump surprises for pharmaceuticals. Unsurprisingly, jumps on earnings-release dates ("earnings" and "revenues") are highly prevalent (see, e.g., Christensen, Timmermann, & Veliyev, 2025), accounting for more than half of the total jump events when combined. However, especially compared to events related to drug development, the difference in average jump surprise is minor between pharmaceuticals and other firms (0% to 0.7%). Finally, the results are qualitatively similar for negative jumps in Panel B of Table 9, with the emphasis shifting towards negative news on drug test results.

Next, to assess the sensitivity of pharmaceutical option returns to recent jump events, I conduct subsample analyses and investigate the performance of the $f^{\text{PHARMA}}$ factor based on EXTRAP. In particular, I differentiate between options on underlyings with high positive jump extrapolation, low negative jump extrapolation, and all other stocks. For the first two subsamples, I use options on underlyings in the top and bottom terciles, respectively, but not on stocks that are in both, to distinguish them from firms with merely elevated volatility. The third subsample consists of stocks outside the top (bottom) positive (negative) EXTRAP tercile. I present the results in Table 10. The subsample of high EXTRAP$^{posjump}$ provides the highest and most significant mean returns and TW+ZHCT alphas. Notably, $f^{\text{PHARMA}}$ yields significantly positive returns in terms of raw mean return but turns insignificant in terms after controlling for risk factors in both the low EXTRAP$^{negjump}$ and residual subsamples. These results indicate that the outperformance of pharmaceutical options tends to be most pronounced and abnormal in terms of option risk factors for underlying stocks that experienced a positive price jump in recent months. This finding aligns with Andreou et al. (2024), who argue that investors might overestimate and overpay for the positive jump propensity of growth-oriented stocks. Similarly, Goyal and Saretto (2009) document that investors tend to overreact to highly positive stock returns, leading to an overestimation of future volatility and an increased demand for options on pharmaceuticals. On the other hand, my findings suggest that negative jumps in pharmaceuticals do not lead to such strong overreaction effects that established risk factors cannot explain.

As a final note, it is worthwhile to highlight that the historical risk premium (HRP) again appears as the option factor most important to explaining returns on $f^{\text{PHARMA}}$ in Table 10. Jumps in pharmaceutical firms related to drug development may provide a complementary explanation for why returns on writing pharmaceutical options are high and why they are linked to HRP, underscoring the persistent outperformance of pharmaceutical options. Although my analyses provide evidence of the effects of demand on the profits of writing options on pharmaceuticals, there remains an additional, distinct risk component to writing these options. In particular, an option writer must consider the risk that pharmaceutical stocks might experience a sharp price jump, resulting in a significant loss on the short option position, which is impossible to negate via delta-hedging. The nature of these jumps related to news on drug development makes this jump risk difficult to quantify with historical information, given the surprise effect associated with such information. In light of this risk, it is plausible to expect that writers of options on pharmaceuticals will demand additional compensation in the form of higher prices for these contracts.[13]

### 5.3. Time-series properties of options on pharmaceuticals

I conclude my analysis by inspecting the time-series properties of options on pharmaceuticals more closely. This approach allows for detecting return patterns in pharmaceutical options, making them and related option anomalies more challenging to explain by option risk factors. Panel A of Figure 5 plots the six-month rolling average return of $f^{\text{PHARMA}}$ and the VRP factor. VRP is among the strongest factors in the space of option returns and tends to capture a large part of the commonality in option returns (see for instance Goyal & Saretto, 2024). As the difference between implied and realized volatility, it proxies for expected returns on delta-neutral positions. Increased ex-ante volatility risk premiums should also reflect the high returns on writing pharmaceutical options. However, comparing the returns of both factors in Figure 5 provides a tentative idea of why VRP is insufficient to explain the returns of the pharmaceutical option factor. Especially before the burst of the technology bubble in the early 2000s, VRP heavily outperformed $f^{\text{PHARMA}}$, and crucially, it exhibited a low correlation with $f^{\text{PHARMA}}$.

[13] In this context, another consideration is asymmetric information and an information risk premium analogous to Easley, Hvidkjaer, and O'hara (2002) when entering an option position. For instance, Ahern (2017) documents illegal insider trading related to tips on clinical trial results. See also Dolgopolov (2009) for a legal discussion of the unique risks market makers face from insider trading in derivatives.

Panel B of Figure 5 includes a scatter plot that visualizes the low correlation between the two factors. Factor return correlations are particularly low over the first half of my subsample with $\rho = 0.05$ compared to $\rho = 0.43$ over the second half.

The low correlation over the first half of the sample can be attributed to the bubble in biotechnology stocks around the turn of the millennium ("genomics bubble"), which manifested in high absolute stock returns for that sector and realized volatility that has not been fully priced into options on these stocks. This dynamic has been especially powerful when the NASDAQ Biotechnology Index (NBI) doubled in 1999 and gained 60% during the first months of the year 2000, one of the rare episodes of options on pharmaceuticals being too cheap a priori (relative to other options) and leading to negative returns on $f^{\text{PHARMA}}$.[14] The plot also shows the monthly volatility of the NBI index based on daily index returns, indicating that around the year 2000, volatility in biotechnology was at a level not even reached during the Global Financial Crisis and the COVID-19 pandemic. On the other hand, VRP exhibited highly positive returns during the early part of my sample and, in contrast to $f^{\text{PHARMA}}$, captured volatility overvaluation at that time. All in all, due to the deviation of $f^{\text{PHARMA}}$ from the profitability of an ex-ante volatility risk premium, VRP is barely correlated with $f^{\text{PHARMA}}$ over the whole sample, which reduces VRP's explanatory power for option strategies influenced by the pharmaceutical industry.

Turning to the second sample half, and particularly to the months following the 2020 pandemic outbreak, $f^{\text{PHARMA}}$ consistently yields positive returns and moves more in lockstep with VRP, indicating that the overpricing of pharmaceutical options is reflected more clearly in their variance risk premiums. The strong increase in the return of $f^{\text{PHARMA}}$ is in line with Jones et al. (2024), who document higher returns from option strategies related to lottery characteristics after the pandemic outbreak. When I compute structural breakpoints in the mean of $f^{\text{PHARMA}}$ using the test by Bai and Perron (1998, 2003), I also determine a breakpoint at the beginning of the year 2020.[15] This result suggests that high returns on pharmaceutical options since 2020 may be driven by increased demand for options on lottery stocks and is also related to the retail frenzy in options with these characteristics (see also Bogousslavsky & Muravyev, 2025; Bryzgalova, Pavlova, & Sikorskaya, 2023).[16]

[14]See also: https://money.cnn.com/2000/03/14/markets/markets_newyork/, accessed on 04/21/2025.

[15]Analogous to Jones et al. (2024), I consider the time period from 2015 to 2022. Figure E1 shows the (raw) $f^{\text{PHARMA}}$ with the indicated breakpoints.

[16]In Figure E2 depicts an analogous analysis to Figure 5 using the first principal components of lottery option anomalies, based on sorting variables like expected idiosyncratic skewness (Boyer, Mitton, & Vorkink, 2010), jackpot probability (Conrad, Kapadia, & Xing, 2014), and maximum stock return (Bali, Cakici, & Whitelaw, 2011; Byun & Kim, 2016). I confirm the high return of lottery options since 2020 and that correlations with

In summary, analyzing time-series properties in returns on pharmaceutical options highlights their relation to lottery-linked demand. The exposure to pharmaceutical options also highlights the dependence of option strategies on distinct patterns, such as sector-specific bubbles and episodes of extreme realized volatility. Such occurrences for options in a given sector contribute to the perceived anomaly of option strategies not fully explained by risk factors in the options market.

## 6. Conclusion

Empirical research on option returns is at an advanced stage, with contributions such as Goyal and Saretto (2024), Horenstein et al. (2024), and Käfer, Moerke, Weigert, and Wiest (2025) examining the abundance or "zoo" of option anomalies. Although these more complex statistical approaches are well-equipped to explain most abnormal option returns, some critical questions remain open. In particular, the observation that sorting options on firm cash holdings produces significantly positive returns for option writers appears as a predominantly robust anomaly without an evident risk-based explanation. In this paper, I build on the insight that options written on pharmaceutical stocks yield highly positive returns, much more so than options in any other industry. Corporate cash holdings constitute a typical feature of pharmaceutical firms and relate to precautionary savings of firms with high growth potential. Consequently, a simple factor that is long in options on pharmaceuticals and short or in other options can largely explain the returns of option anomalies based on characteristics typical of the pharmaceutical industry, such as cash holdings, (low) profitability, (high) market valuation, and investments in intangible assets. My findings extend to a large sample of 140 arbitrary option anomalies based on stock factor characteristics from Jensen et al. (2023). The factor based on pharmaceutical options is not fully explained by established risk factors in the options market and offers additional pricing power over the Zhan et al. (2022) and Tian and Wu (2023) factor models, particularly for anomalies with extreme exposure to pharmaceuticals.

Furthermore, I explore various explanations for the high performance of writing options on pharmaceuticals. In line with Andreou et al. (2024), I document a high demand for options on pharmaceuticals, most likely due to their unique lottery-like features related to news on drug development and clinical trials. Option investors tend to overreact to positive jumps in pharmaceutical stocks, resulting in overvaluation of these options. In addition, the risk of price

$f^{\text{PHARMA}}$ are higher during the second sample half.

jumps related to drug development and trials is hard to predict and quantify with historical return data, possibly demanding a risk premium earned by option writers for being short in these contracts. Finally, the returns on writing pharmaceutical options display distinct time series patterns linked to the bubble in biotechnology stocks in the early 2000s and increased demand for lottery options since 2020, with the former providing an explanations why the returns of the pharmaceutical option factor are not captured by risk factors such as the ex-ante volatility risk premium. My findings contribute to understanding return patterns in the cross-section of equity options and highlight that the abnormal returns of some option strategies are primarily due to the abnormality of options on pharmaceuticals.

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## Figures and tables

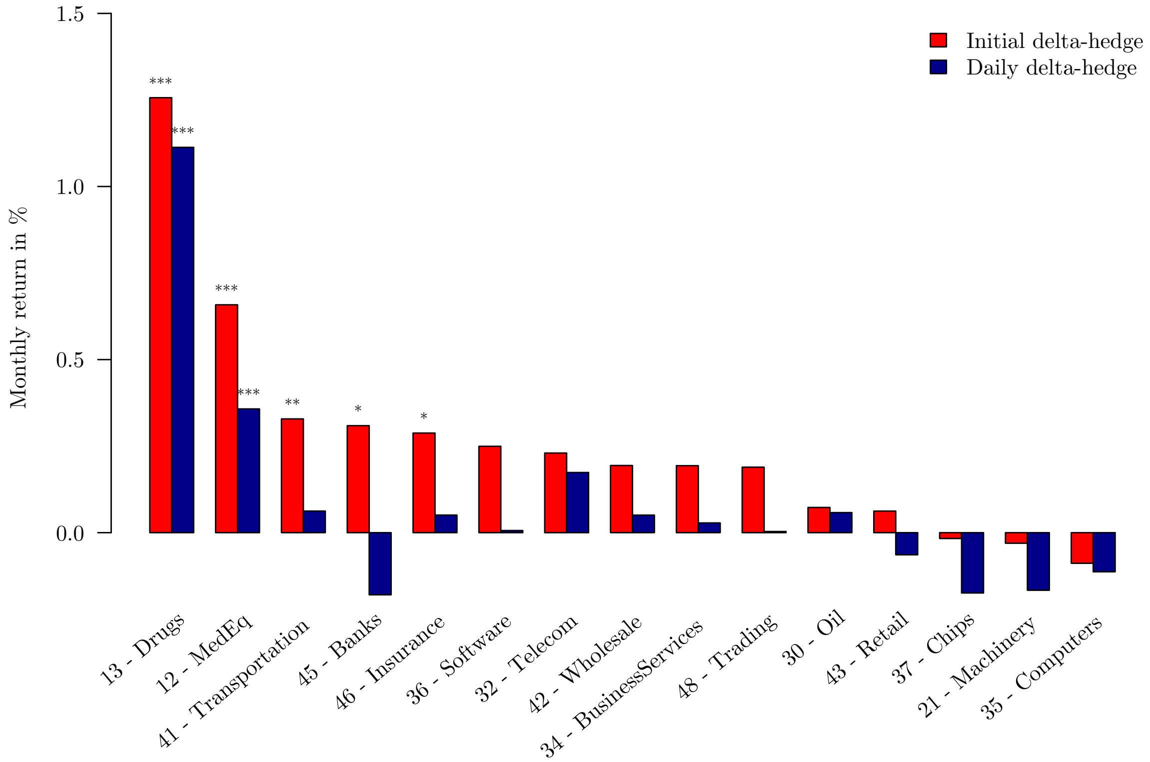



**Fig. 1. Equity option returns by Fama-French 49 industry**

This figure displays average monthly mean returns by industry for writing call options under an initial and daily delta-hedging schedule. Details on option return definitions are in Section 2.3. The industry classification follows Fama and French (1997) with the addition of the computer software industry. Only industries with high option coverage are considered. Significance levels of mean returns are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ based on Newey and West (1987) adjusted standard errors with 4 lags. The sample period is 02-1996 to 12-2022.

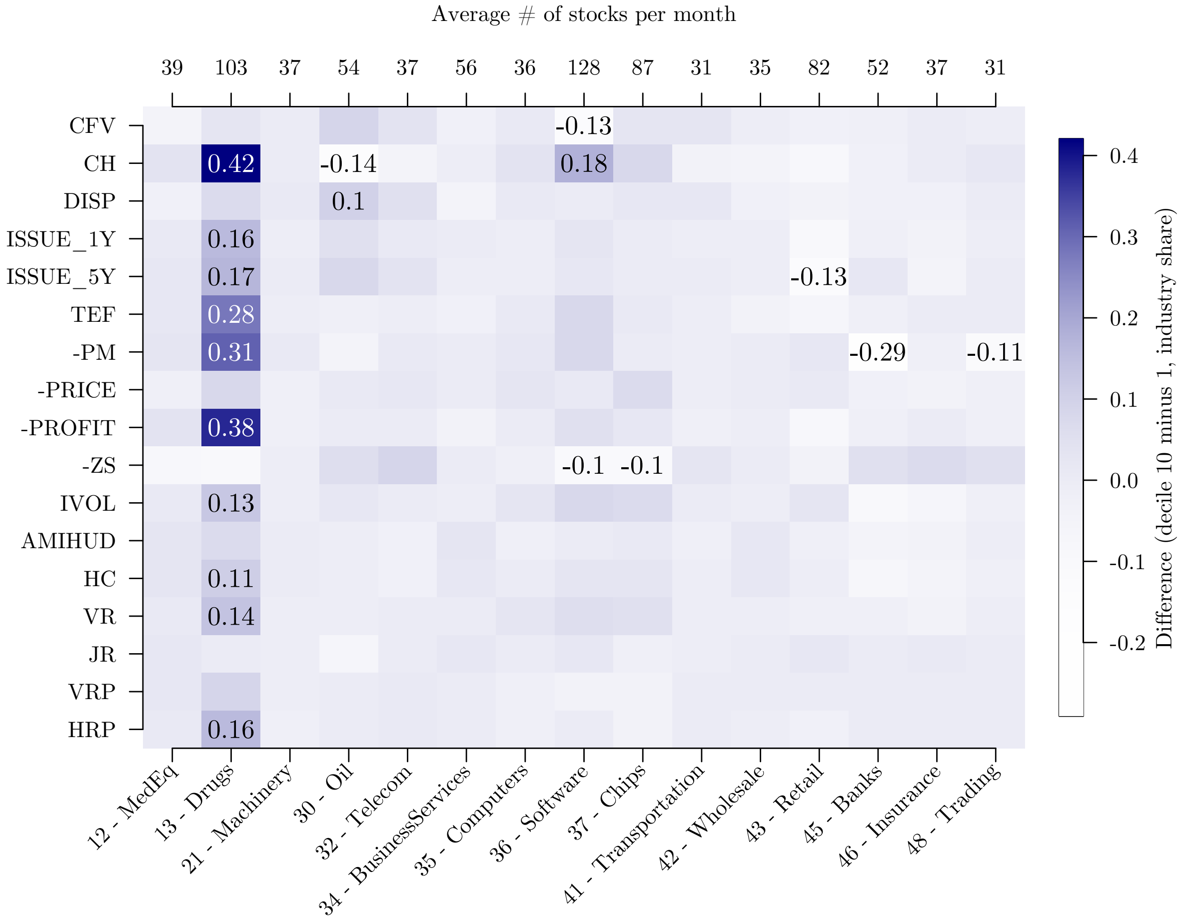



**Fig. 2. Difference of industry share between decile 10 and 1**

This figure shows the average monthly difference between the share of industry $i$ (lower $x$-axis) in decile 10 and decile 1 of anomaly or factor characteristic $j$ ($y$-axis). Red (white) indicates a positive (negative) difference. For the sake of brevity, only differences with an absolute value above 0.1 are displayed numerically. The upper $x$-axis displays the average number of companies by industry per month. The industry classification follows Fama and French (1997) with the addition of the computer software industry. The sorting characteristics are detailed in Internet Appendix B. The sample period is 02-1996 to 12-2022.

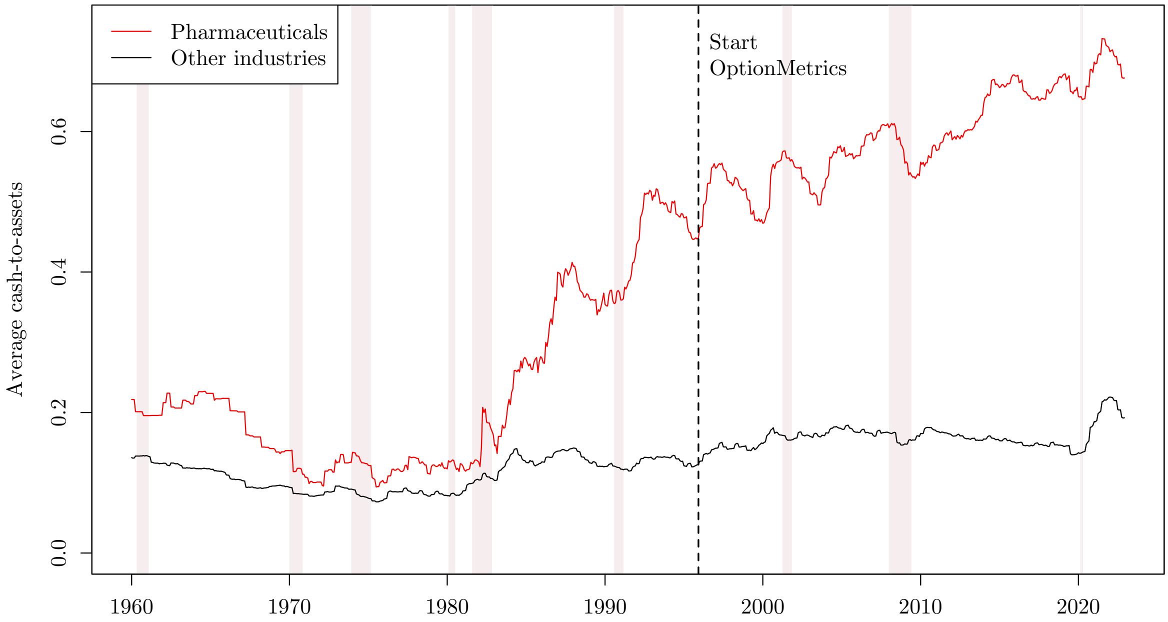



**Fig. 3. Cash-to-assets over time**

This figures plots the average cash-to-assets (CH) ratio for pharmaceutical companies (FF49: 13) and all other industries over time. CH is winsorized at the 0.5% and 99.5% each month. The universe is common stocks traded on the NYSE, AMEX, or NASDAQ exchanges. The data is from Jensen et al. (2023). The sample period is 01-1960 to 12-2022.

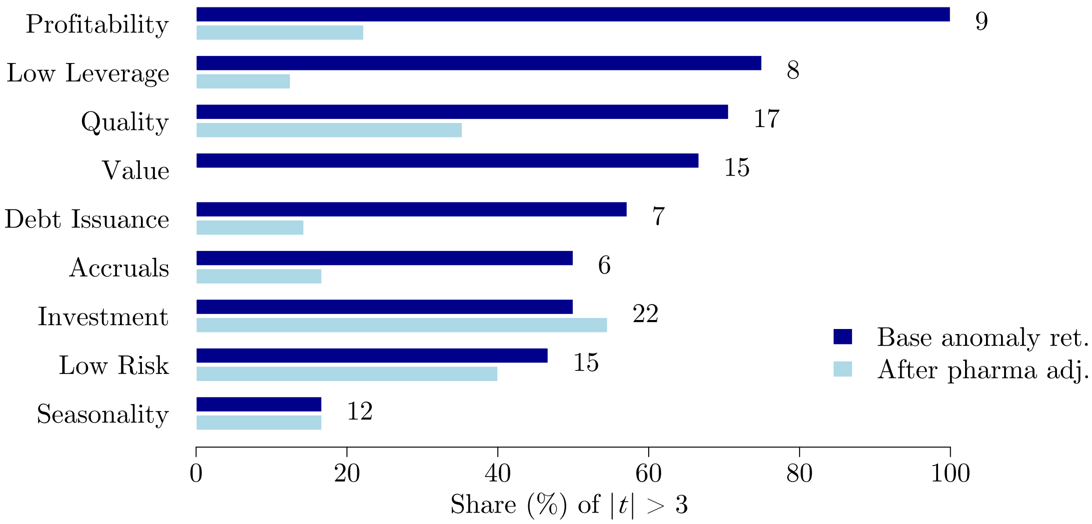



**Fig. 4. Controlling for pharmaceuticals by stock characteristic cluster**

This figure displays the share of significant option anomalies with an absolute $t$-stat above 3, both for anomaly mean returns (dark blue) and alphas when regressing anomalies on $f^{PHARMA}$ (light blue). Results are grouped by clusters of the sorting characteristics. The anomaly characteristics and cluster allocations based on Jensen et al. (2023) are listed in Internet Appendix C.1. $t$-stats are based on Newey and West (1987) adjusted standard errors with 4 lags. The sample period is 02-1996 to 12-2022.

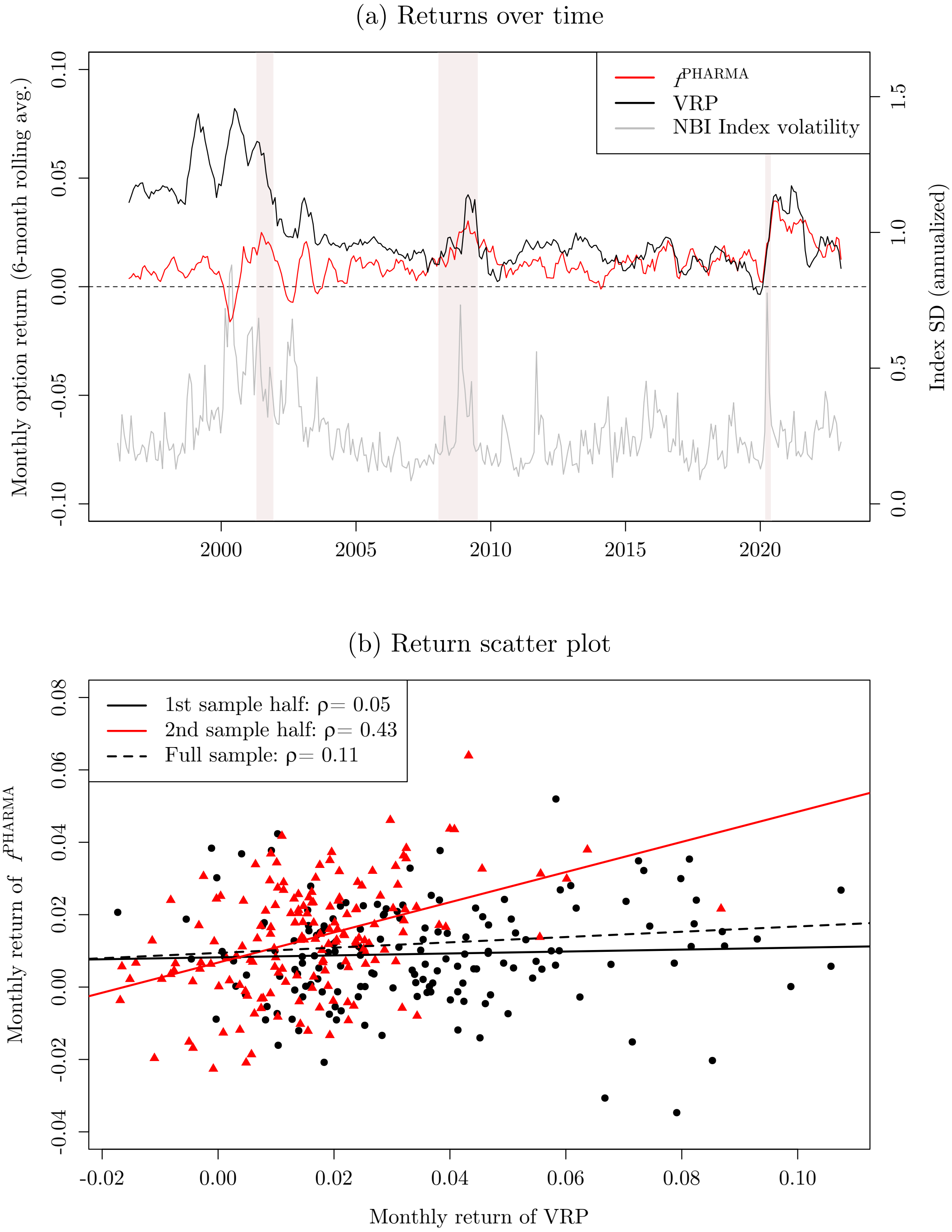



**Fig. 5. Pharmaceutical option factor and VRP**

Panel (a) of this figure plots six-month rolling average returns of the $f^{\text{PHARMA}}$ (red) and VRP (black) factors. The gray line indicates the monthly volatility of the NASDAQ Biotechnology Index (NBI) based on daily index returns. Index prices are from LSEG Workspace. Panel (b) plots individual monthly return observations of $f^{\text{PHARMA}}$ and VRP. Lines are based on fitting a linear regression of $f^{\text{PHARMA}}$ on VRP for the 1st and 2nd sample halves and the full sample. The sample period is 02-1996 to 12-2022.

## Table 1: Pooled summary statistics of options data

This table reports pooled summary statistics of month-end to month-end call options data. The sample period is from 02-1996 to 12-2022. Initially delta-hedged returns are based on a hedge that is held constant until the position is closed. Daily delta-hedged option returns are the monthly returns of a delta-hedged call position adjusted daily to be immune to changes in the underlying. Details on the return definitions are outlined in Section 2.3. Delta and vega are option Greeks as provided by OptionMetrics. Moneyness is the ratio of the option's strike price ($K$) to the underlying stock price ($S$) in percent. Time to maturity is the days until the option's expiration. The quoted option bid-ask spread is proportional to the option mid price in percent.

| Variable | Mean | SD | $10^{th}$ | $25^{th}$ | Median | $75^{th}$ | $90^{th}$ |
|---|---|---|---|---|---|---|---|
| Return on initially delta-hedged call (%) | 0.25 | 9.77 | -8.38 | -1.83 | 1.75 | 4.43 | 7.67 |
| Return on daily delta-hedged call (%) | 0.09 | 5.6 | -4.53 | -1.38 | 0.53 | 2.29 | 4.58 |
| Delta | 0.54 | 0.11 | 0.39 | 0.47 | 0.54 | 0.61 | 0.68 |
| Vega | 0.14 | 0.01 | 0.13 | 0.14 | 0.14 | 0.15 | 0.15 |
| Moneyness ($K/S$, %) | 100.22 | 5.21 | 94.27 | 97.56 | 100.12 | 102.86 | 106.32 |
| Time to maturity (in days) | 49.65 | 2.08 | 46 | 49 | 50 | 51 | 52 |
| Quoted option bid-ask spread (%) | 16.48 | 11.26 | 4.8 | 8 | 13.33 | 22.22 | 33.33 |
| Observations: | 393,229 | | | | | | |

## Table 2: Mean returns of option long-short portfolios

This table shows the monthly mean returns of option anomalies and risk factors. Option returns are from the perspective of an option writer under an initial and daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percentage. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. Option anomalies following Zhan et al. (2022) are in Panel A; option risk factors following Zhan et al. (2022) and Tian and Wu (2023) are in Panel B. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | Initial hedge | Daily hedge |
|---|---|---|
| | (1) | (2) |
| Panel A: ZHCT anomalies | | |
| Cash-to-assets ratio (CH) | 0.80 | 0.80 |
| | (4.15) | (7.17) |
| Cash flow variance (CFV) | 0.02 | 0.64 |
| | (0.14) | (5.57) |
| Analyst earnings forecast dispersion (DISP) | 0.00 | 0.31 |
| | (0.01) | (4.36) |
| One-year new issues (ISSUE_1Y) | 0.30 | 0.41 |
| | (2.03) | (4.02) |
| Five-year new issues (ISSUE_5Y) | 0.42 | 0.57 |
| | (2.76) | (5.96) |
| Total external financing (TEF) | 0.44 | 0.53 |
| | (2.76) | (4.99) |
| -Profit margin (-PM) | 0.43 | 0.87 |
| | (2.83) | (8.35) |
| -Stock price (-PRICE) | 0.62 | 1.01 |
| | (3.16) | (7.01) |
| -Operating profitability (-PROFIT) | 0.53 | 0.77 |
| | (3.11) | (7.79) |
| -Z-score (-ZS) | -0.18 | 0.23 |
| | (-1.37) | (2.36) |
| Panel B: Risk factors | | |
| Idiosyncratic volatility (IVOL) | 0.85 | 0.81 |
| | (4.75) | (6.45) |
| Stock illiquidity (AMIHUD) | 0.13 | 0.47 |
| | (0.87) | (3.63) |
| Delta-hedging cost (HC) | 0.53 | 0.80 |
| | (3.41) | (6.15) |
| Volatility risk (VR) | 0.93 | 1.02 |
| | (6.16) | (8.53) |
| Jump risk (JR) | 0.78 | 0.87 |
| | (6.77) | (11.68) |
| Volatility risk premium (VRP) | 2.60 | 2.54 |
| | (10.87) | (11.42) |
| Historical risk premium (HRP) | 0.71 | 1.12 |
| | (6.38) | (9.48) |

## Table 3: Alphas of long-short option returns after risk adjustments

This table shows alphas of option strategies after regressing ZHCT anomaly returns on option risk factors by ZHCT and TW. TW+ZHCT adds the IVOL factor to the five TW risk factors. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percentage. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | (1) | (2) | (3) |
|---|---|---|---|
| | ZHCT | TW | TW+ZHCT |
| CH | 0.44 | 0.68 | 0.36 |
| | (3.87) | (5.26) | (2.73) |
| CFV | 0.31 | -0.06 | -0.08 |
| | (2.94) | (-0.58) | (-0.78) |
| DISP | 0.01 | 0.21 | 0.12 |
| | (0.21) | (2.18) | (1.20) |
| ISSUE_1Y | 0.00 | 0.46 | 0.14 |
| | (0.07) | (3.84) | (1.36) |
| ISSUE_5Y | 0.20 | 0.35 | 0.11 |
| | (2.80) | (3.50) | (1.00) |
| TEF | 0.08 | 0.43 | 0.05 |
| | (0.94) | (3.54) | (0.47) |
| -PM | 0.39 | 0.37 | 0.08 |
| | (3.75) | (3.32) | (0.75) |
| -PRICE | 0.44 | 0.19 | 0.21 |
| | (5.14) | (1.60) | (2.09) |
| -PROFIT | 0.27 | 0.37 | 0.10 |
| | (3.63) | (3.53) | (1.00) |
| -ZS | 0.31 | -0.18 | 0.05 |
| | (2.27) | (-1.29) | (0.37) |

## Table 4: Pharmaceutical option factor: performance and risk loadings

This table shows the mean returns, TW+ZHCT alphas, and TW+ZHCT factor loadings of the pharmaceutical option factor, $f^{\text{PHARMA}}$, which invests long in options on pharmaceuticals and is short in options on all other stocks. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. The baseline $f^{\text{PHARMA}}$ in columns 1 and 2 is based on equal-weighting options in the long and short portfolios. For robustness, columns 3 and 4 report results when weighting options by their option market value, which is the option's open interest capped at the monthly $80^{\text{th}}$ percentile, following Jensen et al. (2023); Käfer, Moerke, and Wiest (2025) to avoid a few stocks with extreme option activity dominating the sample. Columns 5 and 6 exclude illiquid options with a proportional option bid-ask spread below the monthly median. Risk factors are constructed using the same weighting scheme and filters as $f^{\text{PHARMA}}$. Returns and alphas are in percent. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | Equal weight | | Option value weight | | Low options spreads | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $f^{\text{PHARMA}}$ mean, $\alpha$ | 1.129 | 0.456 | 1.051 | 0.453 | 0.81 | 0.462 |
| | (10.63) | (3.34) | (9.6) | (2.85) | (8.01) | (3.65) |
| IVOL | | 0.233 | | -0.01 | | -0.125 |
| | | (2.36) | | (-0.12) | | (-1.48) |
| HC | | -0.093 | | 0.051 | | 0.31 |
| | | (-1.14) | | (0.92) | | (3.85) |
| VR | | 0.076 | | 0.15 | | 0.09 |
| | | (0.85) | | (1.75) | | (0.9) |
| JR | | 0.055 | | -0.048 | | 0.02 |
| | | (0.7) | | (-0.64) | | (0.22) |
| VRP | | -0.002 | | 0.011 | | -0.045 |
| | | (-0.05) | | (0.22) | | (-0.84) |
| HRP | | 0.406 | | 0.265 | | 0.183 |
| | | (7.03) | | (5.64) | | (3.5) |
| Adj. $R^2$ | | 0.21 | | 0.175 | | 0.119 |

## Table 5: Long-short option returns after adjustment for $f^{\text{PHARMA}}$

This table shows mean returns and alphas of option strategies after regressing ZHCT anomaly returns on the pharmaceutical option factor, $f^{\text{PHARMA}}$, and industry-demeaned ZHCT and TW factors, denoted by "*". $f^{\text{PHARMA}}$ invests long in options on pharmaceuticals and is short in options on all other stocks. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percentage. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* +$f^{\text{PHARMA}}$ |
| CH | 0.80 | 0.04 | 0.63 | 0.18 |
| | (7.17) | (0.47) | (5.70) | (1.72) |
| CFV | 0.64 | 0.63 | -0.09 | -0.06 |
| | (5.57) | (4.16) | (-0.80) | (-0.58) |
| DISP | 0.31 | 0.33 | 0.03 | 0.08 |
| | (4.36) | (3.77) | (0.32) | (0.72) |
| ISSUE_1Y | 0.41 | 0.09 | 0.26 | 0.11 |
| | (4.02) | (1.17) | (2.53) | (1.03) |
| ISSUE_5Y | 0.57 | 0.25 | 0.29 | 0.15 |
| | (5.96) | (2.37) | (2.78) | (1.55) |
| TEF | 0.53 | -0.03 | 0.24 | -0.04 |
| | (4.99) | (-0.27) | (2.50) | (-0.37) |
| -PM | 0.87 | 0.23 | 0.32 | -0.04 |
| | (8.35) | (2.17) | (2.87) | (-0.41) |
| -PRICE | 1.01 | 0.93 | 0.25 | 0.23 |
| | (7.01) | (4.24) | (2.47) | (2.08) |
| -PROFIT | 0.77 | 0.16 | 0.30 | -0.04 |
| | (7.79) | (1.50) | (2.71) | (-0.40) |
| -ZS | 0.23 | 0.28 | -0.01 | -0.03 |
| | (2.36) | (2.80) | (-0.11) | (-0.19) |

## Table 6: Growth potential and pharmaceutical firms

Panel A of this table summarizes monthly average mean growth potential characteristics for pharmaceutical and other underlying stocks. The construction and definitions of characteristics are detailed in Internet Appendix B.3. All characteristics are cross-sectionally winsorized at the 0.5% and 99.5% levels. The last column indicates the difference between the share of pharmaceuticals in decile 10 and decile 1, analogous to Figure 2. Panel B shows mean returns and alphas of option strategies formed on the growth potential variables in Panel A. I regress anomaly returns on the pharmaceutical option factor, $f^{\text{PHARMA}}$, industry-demeaned ZHCT and TW factors (denoted by "*"), and industry-*unadjusted* ZHCT and TW factors. $f^{\text{PHARMA}}$ invests long in options on pharmaceuticals and is short in options on all other stocks. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percent. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

Panel A: Average growth potential characteristics

| | Pharma | Other | Diff. mean | Pharma Share$^{10-1}$ |
|---|---|---|---|---|
| Growth potential (GO) | 1.25 | 0.33 | 0.92 | 29% |
| | | | (14.06) | (24.13) |
| Cash-flow-to-price (CFP) | -0.02 | 0.09 | -0.10 | -34% |
| | | | (-35.43) | (-23.28) |
| Mkt. value to book value of assets (MABA) | 4.93 | 2.55 | 2.38 | 25% |
| | | | (20.00) | (25.02) |
| R&D to assets (RD_AT) | 0.24 | 0.06 | 0.18 | 59% |
| | | | (54.17) | (45.05) |
| R&D intensity (RD_SALES) | 9.39 | 0.3 | 9.09 | 70% |
| | | | (6.69) | (47.36) |

Panel B: Portfolio sorts based on growth potential variables

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* +$f^{\text{PHARMA}}$ | TW+ZHCT full |
| GO | 0.71 | 0.13 | 0.37 | 0.03 | 0.17 |
| | (7.70) | (1.81) | (3.07) | (0.28) | (1.53) |
| -CFP | 0.78 | 0.04 | 0.51 | 0.06 | 0.22 |
| | (7.38) | (0.52) | (4.64) | (0.61) | (2.04) |
| MABA | 0.25 | -0.33 | 0.55 | 0.20 | 0.29 |
| | (1.67) | (-2.27) | (3.86) | (1.32) | (1.91) |
| RD_AT | 1.09 | 0.02 | 0.67 | 0.00 | 0.43 |
| | (8.23) | (0.18) | (3.90) | (0.03) | (2.40) |
| RD_SALE | 1.16 | 0.10 | 0.77 | 0.11 | 0.49 |
| | (9.16) | (0.90) | (5.19) | (0.83) | (3.21) |

**Table 7: Summary of the option anomaly zoo and the impact of $f^{\text{PHARMA}}$**

This table summarizes the profitability and significance of option anomalies based on stock characteristics from Jensen et al. (2023). The full sorting variable list is provided in Internet Appendix C.1. In Internet Appendix C.2, I provide the mean returns and alphas of the individual option strategies that underlie this table. The columns present the number of anomalies considered (N), the average absolute 10-minus-1 anomaly mean return and alpha ($|\bar{R}|$, $|\alpha|$), the average absolute $t$-stat of anomaly means or alphas ($|t|$), the share of absolute $t$-stats above 3 ($|t| > 3$), and the average adjusted $R^2$ value of regressing anomaly returns on option factors. Panels B and C summarize anomaly subsamples (comprising 50 anomalies) based on sorting characteristics with a high or low pharmaceutical exposure, which is determined with the absolute difference between the share of pharmaceuticals in decile 10 and 1, analogous to Figure 2. $t$-stats are based on Newey and West (1987) adjusted standard errors with 4 lags. The sample period is 02-1996 to 12-2022.

| | N | $\lvert\bar{R}\rvert$, $\lvert\alpha\rvert$ | $\lvert t\rvert$ | $\lvert t\rvert > 3$ | Adj. $R^2$ |
|---|---|---|---|---|---|
| Panel A: All test long-short portfolios | | | | | |
| Mean return | 140 | 0.33 | 3.54 | 48% | - |
| Alpha $f^{\text{PHARMA}}$ | 140 | 0.19 | 2.07 | 23% | 0.06 |
| Alpha TW*+ZHCT* | 140 | 0.21 | 1.91 | 24% | 0.23 |
| Alpha TW*+ZHCT*+$f^{\text{PHARMA}}$ | 140 | 0.13 | 1.22 | 3% | 0.27 |
| Alpha TW+ZHCT full | 140 | 0.16 | 1.43 | 8% | 0.27 |
| Panel B: Portfolios with high pharmaceutical exposure | | | | | |
| Mean return | 50 | 0.61 | 5.83 | 84% | - |
| Alpha $f^{\text{PHARMA}}$ | 50 | 0.24 | 2.28 | 26% | 0.16 |
| Alpha TW*+ZHCT* | 50 | 0.31 | 2.70 | 44% | 0.35 |
| Alpha TW*+ZHCT*+$f^{\text{PHARMA}}$ | 50 | 0.11 | 1.03 | 2% | 0.45 |
| Alpha TW+ZHCT full | 50 | 0.17 | 1.47 | 10% | 0.41 |
| Panel C: Portfolios with low pharmaceutical exposure | | | | | |
| Mean return | 50 | 0.14 | 1.94 | 20% | - |
| Alpha $f^{\text{PHARMA}}$ | 50 | 0.13 | 1.66 | 16% | 0.01 |
| Alpha TW*+ZHCT* | 50 | 0.14 | 1.39 | 6% | 0.13 |
| Alpha TW*+ZHCT*+$f^{\text{PHARMA}}$ | 50 | 0.13 | 1.29 | 2% | 0.14 |
| Alpha TW+ZHCT full | 50 | 0.14 | 1.34 | 6% | 0.15 |

## Table 8: Option demand for stocks on pharmaceuticals

This table shows the results of cross-sectional Fama-MacBeth (1973) of option demand measures on an indicator variable (PHARMA) equal to 1 for options on pharmaceuticals, and 0 otherwise. The four dependent variables are month-end option open interest (OI) scaled by the underlying stock's shares outstanding, OI scaled by stock volume over the prior month, option volume (OVOL) scaled by stock volume over the prior month, and net open interest (NOI) scaled by shares outstanding. NOI is based on NASDAQ ISE signed volume data and defined in Equation (5). All open interest and option volume measures are aggregated at the stock level across all call contracts. As controls, I use the natural logarithm of the underlying stock's market capitalization (SIZE) and various other characteristics outlined in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022 for columns 1 to 6. The sample period in columns 7 and 8 for NOI is 05-2005 to 11-2020.

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | OI / Shares Out. | | OI / Stock Vol. | | OVOL / Stock Vol. | | Net OI / Shares Out. | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PHARMA | 0.111 | 0.042 | 0.038 | 0.032 | 0.021 | 0.011 | 0.086 | 0.08 |
| | (8.62) | (2.83) | (9.71) | (8.47) | (6.73) | (2.85) | (2.73) | (2.85) |
| SIZE | | 0.028 | | 0.009 | | 0.026 | | -0.022 |
| | | (17.06) | | (13.12) | | (12.14) | | (-4.41) |
| IVOL | | 7.818 | | 0.163 | | 1.591 | | -0.674 |
| | | (15.12) | | (2.16) | | (10.8) | | (-0.71) |
| VR | | 0.843 | | 0.17 | | 0.288 | | 0.103 |
| | | (6.35) | | (6.21) | | (12.8) | | (0.23) |
| VRP | | -0.109 | | 0.018 | | 0.009 | | 0.792 |
| | | (-3.93) | | (3.56) | | (1.57) | | (6.24) |
| GO | | 0.03 | | 0.009 | | 0.01 | | -0.021 |
| | | (7.04) | | (8.35) | | (7.7) | | (-3.8) |
| Intercept | 0.177 | -0.244 | 0.064 | -0.017 | 0.065 | -0.188 | -0.042 | 0.182 |
| | (24.17) | (-15.53) | (41.56) | (-2.9) | (22.24) | (-10.01) | (-3.05) | (2.98) |
| Adj. $R^2$ | 0.011 | 0.125 | 0.019 | 0.058 | 0.01 | 0.11 | 0.001 | 0.018 |

## Table 9: News categories and jump surprises

This table summarizes average jump surprise returns ($\bar{R}_{JS}$) on jump days for pharmaceutical and other firms. The results are pooled across all jump days (first row) and grouped by news categories. News data is from RavenPack News Analytics, and individual headlines are linked to jump surprises by the day of the news event and the jump surprise. Details on the filtering and construction of the RavenPack news sample are provided in Internet Appendix D.1. Jump days are identified as days when the daily raw stock return exceeds the EWMA-conditional volatility by a factor of 3. $\bar{R}_{JS}$ is measured as the difference between the return on jump day $t$ and the jump extrapolation measure (EXTRAP) defined in Equation (6). The columns present the number of distinct news events (N), share of total news by news group, and $\bar{R}_{JS}$. The last column includes the difference between $\bar{R}_{JS}$ for pharmaceutical and other firms. Panel A (B) shows news events on positive (negative) jump days. The sample period is 01-2000 to 10-2022.

| | Pharmaceutical firms | | | Other firms | | | |
|---|---|---|---|---|---|---|---|
| Group | N | Share | $\bar{R}_{JS}$ | N | Share | $\bar{R}_{JS}$ | Diff. $\bar{R}_{JS}$ |
| Panel A: Positive jumps | | | | | | | |
| All | 8,334 | | 13.8% | 118,731 | | 10.3% | **3.5%** |
| Products-services | 1,188 | 14% | 23.2% | 4,494 | 4% | 11.8% | **11.4%** |
| Acquisitions-mergers | 469 | 6% | 20.1% | 5,550 | 5% | 12.6% | **7.5%** |
| Investor-relations | 378 | 5% | 19.4% | 4,225 | 4% | 9.9% | **9.5%** |
| Partnerships | 140 | 2% | 18.5% | 855 | 1% | 11.3% | **7.2%** |
| Technical-analysis | 386 | 5% | 12.6% | 4,085 | 3% | 7.8% | **4.8%** |
| Labor-issues | 224 | 3% | 12.4% | 2,916 | 2% | 10.6% | **1.9%** |
| Marketing | 111 | 1% | 12.3% | 597 | 1% | 8.5% | **3.8%** |
| Insider-trading | 462 | 6% | 11% | 3,365 | 3% | 8.8% | **2.2%** |
| Earnings | 2,939 | 35% | 10.9% | 54,287 | 46% | 10.2% | **0.7%** |
| Revenues | 1,767 | 21% | 10.4% | 34,127 | 29% | 10.4% | **0%** |
| Panel B: Negative jumps | | | | | | | |
| All | 6,758 | | -12.6% | 103,670 | | -10.3% | **-2.3%** |
| Products-services | 649 | 10% | -19.3% | 3,047 | 3% | -9.1% | **-10.2%** |
| Investor-relations | 317 | 5% | -14.5% | 3,788 | 4% | -9.9% | **-4.6%** |
| Labor-issues | 233 | 3% | -14% | 3,244 | 3% | -10.6% | **-3.3%** |
| Revenues | 1,598 | 24% | -11.8% | 30,035 | 29% | -11.1% | **-0.7%** |
| Earnings | 2,776 | 41% | -11.7% | 47,410 | 46% | -10.7% | **-1.1%** |
| Technical-analysis | 266 | 4% | -10.8% | 4,654 | 4% | -7.6% | **-3.2%** |
| Insider-trading | 271 | 4% | -10.4% | 3,260 | 3% | -8% | **-2.4%** |
| Acquisitions-mergers | 257 | 4% | -9.8% | 3,434 | 3% | -8.1% | **-1.6%** |

**Table 10: Pharmaceutical option factor: subsamples based on jump extrapolation**

This table shows the mean returns, TW+ZHCT alphas and factor loadings of the pharmaceutical option factor, $f^{\text{PHARMA}}$, for subsamples based on the jump return extrapolation measure defined in Equation (6). Columns 1 and 2 show results for options on stock in the month's highest tercile of EXTRAP$^{posjump}$ (and outside of the EXTRAP$^{negjump}$ bottom-tercile). Columns 3 and 4 show results for options on stock in the month's lowest tercile of EXTRAP$^{negjump}$ (and outside of the EXTRAP$^{posjump}$ top-tercile). Columns 5 and 6 use options on stock in neither EXTRAP$^{posjump}$ top-tercile nor EXTRAP$^{negjump}$ bottom-tercile. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. The last rows (Diff. EXTRAP$^{posjump}$) display differences between mean returns and alphas for the high EXTRAP$^{posjump}$ and columns 3 to 6. Returns and alphas are in percent. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | High EXTRAP$^{posjump}$ | | Low EXTRAP$^{negjump}$ | | All other stocks | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $f^{\text{PHARMA}}$ mean, $\alpha$ | 1.45 | 0.858 | 0.994 | 0.186 | 0.731 | 0.253 |
| | (10.71) | (4.02) | (6.84) | (0.8) | (6.91) | (1.62) |
| IVOL | | 0.021 | | 0.412 | | 0.096 |
| | | (0.17) | | (2.8) | | (0.94) |
| HC | | -0.027 | | -0.29 | | -0.113 |
| | | (-0.27) | | (-2.61) | | (-1.14) |
| VR | | 0.18 | | -0.038 | | 0.162 |
| | | (1.32) | | (-0.26) | | (1.53) |
| JR | | 0.044 | | 0.025 | | 0.046 |
| | | (0.42) | | (0.2) | | (0.61) |
| VRP | | -0.027 | | 0.082 | | 0.018 |
| | | (-0.37) | | (1.19) | | (0.32) |
| HRP | | 0.399 | | 0.489 | | 0.238 |
| | | (4.74) | | (5.44) | | (3.15) |
| Adj. $R^2$ | | 0.083 | | 0.117 | | 0.061 |
| Diff. EXTRAP$^{posjump}$ | | | 0.456 | 0.672 | 0.719 | 0.605 |
| | | | (3.4) | (2.55) | (5.97) | (2.51) |

Options on Drugs:
Industry Exposure and Option Anomalies

Internet Appendix

(Not for publication)

# A Additional figures and tables

## Table A1: Initially delta-hedged long-short portfolios (sample period: 02-1996 to 05-2016)

This table shows the monthly mean returns of option anomalies and risk factors. Option returns are from the perspective of an option writer under an *initial* delta-hedging schedule. The sample period is the same as in ZHCT: 02-1996 to 05-2016 (I denote sample months by return months, whereas ZHCT use portfolio formation months). I report anomaly returns based on my option sample, the feasible strategy returns in Duarte, Jones, Mo, and Khorram (2024) (DJMK), and the infeasible original ZHCT strategy returns. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percent. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses for the anomaly returns used throughout this paper. Standard errors and mean returns of option strategies for the DJMK and ZHCT samples are reported as stated in the respective reference papers.

| | Initial hedge | DJMK | ZHCT |
|---|---|---|---|
| CH | 0.53 | 0.60 | 2.11 |
| | (2.42) | (2.60) | (15.88) |
| CFV | 0.06 | -0.13 | 1.63 |
| | (0.43) | (-0.94) | (11.74) |
| DISP | -0.04 | -0.11 | 2.03 |
| | (-0.29) | (-0.69) | (19.81) |
| ISSUE_1Y | 0.04 | 0.20 | 1.60 |
| | (0.25) | (1.59) | (14.84) |
| ISSUE_5Y | 0.16 | 0.31 | 1.86 |
| | (1.16) | (2.14) | (19.92) |
| TEF | 0.14 | 0.01 | 1.87 |
| | (0.85) | (0.08) | (14.63) |
| -PM | 0.18 | 0.12 | 2.53 |
| | (1.07) | (0.66) | (22.11) |
| -PRICE | 0.73 | 0.61 | 5.01 |
| | (3.39) | (2.74) | (33.23) |
| -PROFIT | 0.30 | 0.10 | 2.48 |
| | (1.57) | (0.54) | (21.67) |
| -ZS | -0.09 | 0.10 | 2.60 |
| | (-0.60) | (0.58) | (20.11) |
| IVOL | 0.68 | 0.77 | 3.88 |
| | (3.33) | (3.75) | (28.24) |
| AMIHUD | 0.27 | 0.22 | 3.79 |
| | (1.79) | (1.21) | (30.85) |
| VRP (-VOL_deviation) | 2.94 | 2.81 | 4.48 |
| | (10.18) | (11.53) | (16.72) |

## Table A2: Individual decile returns of option long-short portfolios

This table shows the monthly mean returns of decile portfolios based on option anomaly and risk factor characteristics in ZHCT and TW. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. All portfolios are equally weighted, with average returns in percent. A minus sign indicates that some strategies inversely sort on the given characteristic. Option anomalies following Zhan et al. (2022) are in Panel A; option risk factors following Zhan et al. (2022) and Tian and Wu (2023) are in Panel B. The sorting characteristics are detailed in Internet Appendix B. *t*-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: ZHCT anomalies | | | | | | | | | | | |
| CH | -0.05 | -0.08 | -0.01 | -0.01 | 0.02 | 0.01 | -0.01 | 0.04 | 0.13 | 0.75 | 0.80 |
| | (-0.38) | (-0.65) | (-0.08) | (-0.06) | (0.15) | (0.08) | (-0.10) | (0.29) | (1.01) | (5.13) | (7.17) |
| CFV | -0.15 | -0.06 | -0.03 | -0.05 | 0.00 | 0.06 | 0.05 | 0.16 | 0.34 | 0.49 | 0.64 |
| | (-1.26) | (-0.53) | (-0.26) | (-0.48) | (0.03) | (0.47) | (0.41) | (1.32) | (2.57) | (3.11) | (5.57) |
| DISP | -0.04 | -0.04 | -0.06 | -0.06 | -0.04 | -0.01 | 0.02 | 0.20 | 0.23 | 0.27 | 0.31 |
| | (-0.40) | (-0.42) | (-0.50) | (-0.55) | (-0.34) | (-0.04) | (0.16) | (1.54) | (1.76) | (1.94) | (4.36) |
| ISSUE_1Y | 0.03 | 0.02 | 0.02 | 0.02 | 0.03 | -0.03 | 0.03 | 0.01 | 0.23 | 0.44 | 0.41 |
| | (0.24) | (0.20) | (0.23) | (0.15) | (0.28) | (-0.19) | (0.22) | (0.05) | (1.68) | (2.80) | (4.02) |
| ISSUE_5Y | -0.01 | -0.01 | -0.04 | -0.02 | -0.04 | 0.01 | 0.00 | -0.01 | 0.26 | 0.56 | 0.57 |
| | (-0.11) | (-0.06) | (-0.35) | (-0.20) | (-0.32) | (0.09) | (-0.02) | (-0.09) | (2.05) | (3.77) | (5.96) |
| TEF | 0.09 | 0.03 | 0.01 | 0.02 | -0.05 | -0.06 | 0.01 | 0.02 | 0.10 | 0.62 | 0.53 |
| | (0.73) | (0.28) | (0.10) | (0.15) | (-0.47) | (-0.49) | (0.08) | (0.17) | (0.76) | (3.93) | (4.99) |
| -PM | -0.02 | -0.01 | -0.04 | -0.03 | -0.04 | -0.01 | -0.04 | -0.07 | 0.03 | 0.85 | 0.87 |
| | (-0.19) | (-0.10) | (-0.37) | (-0.25) | (-0.39) | (-0.10) | (-0.37) | (-0.52) | (0.25) | (5.30) | (8.35) |
| -PRICE | -0.11 | -0.06 | -0.10 | -0.10 | -0.11 | -0.10 | -0.05 | 0.16 | 0.37 | 0.90 | 1.01 |
| | (-0.98) | (-0.59) | (-0.91) | (-0.91) | (-0.92) | (-0.90) | (-0.37) | (1.23) | (2.53) | (4.96) | (7.01) |
| -PROFIT | 0.05 | -0.05 | -0.01 | -0.03 | -0.07 | -0.06 | -0.04 | 0.02 | 0.14 | 0.82 | 0.77 |
| | (0.44) | (-0.46) | (-0.11) | (-0.31) | (-0.65) | (-0.51) | (-0.34) | (0.17) | (0.96) | (5.00) | (7.79) |
| -ZS | 0.25 | -0.02 | 0.00 | -0.06 | -0.02 | 0.05 | 0.02 | 0.05 | 0.15 | 0.48 | 0.23 |
| | (1.74) | (-0.14) | (0.00) | (-0.52) | (-0.14) | (0.42) | (0.20) | (0.44) | (1.16) | (3.37) | (2.36) |
| Panel B: ZHCT & TW factors | | | | | | | | | | | |
| IVOL | -0.02 | -0.04 | -0.06 | -0.07 | -0.07 | -0.06 | -0.02 | 0.05 | 0.29 | 0.79 | 0.81 |
| | (-0.18) | (-0.43) | (-0.59) | (-0.61) | (-0.65) | (-0.49) | (-0.15) | (0.37) | (1.87) | (4.70) | (6.45) |
| AMIHUD | -0.04 | -0.03 | -0.05 | 0.02 | 0.00 | 0.06 | 0.03 | 0.10 | 0.28 | 0.43 | 0.47 |
| | (-0.40) | (-0.28) | (-0.46) | (0.14) | (0.03) | (0.46) | (0.25) | (0.79) | (1.98) | (2.61) | (3.63) |
| HC | -0.07 | -0.05 | -0.07 | -0.04 | -0.09 | -0.02 | 0.03 | 0.08 | 0.30 | 0.73 | 0.80 |
| | (-0.73) | (-0.49) | (-0.64) | (-0.32) | (-0.70) | (-0.16) | (0.22) | (0.57) | (2.24) | (4.34) | (6.15) |
| VR | -0.14 | -0.16 | -0.11 | -0.14 | -0.15 | -0.05 | 0.04 | 0.17 | 0.45 | 0.89 | 1.02 |
| | (-1.36) | (-1.55) | (-1.05) | (-1.24) | (-1.30) | (-0.42) | (0.31) | (1.19) | (3.23) | (5.24) | (8.53) |
| JR | -0.14 | -0.14 | -0.07 | -0.04 | -0.04 | 0.01 | 0.10 | 0.14 | 0.23 | 0.73 | 0.87 |
| | (-0.87) | (-1.13) | (-0.61) | (-0.36) | (-0.36) | (0.11) | (0.84) | (1.14) | (1.85) | (5.35) | (11.68) |
| VRP | -0.52 | -0.52 | -0.34 | -0.23 | -0.19 | -0.06 | 0.04 | 0.16 | 0.42 | 2.02 | 2.54 |
| | (-2.99) | (-3.49) | (-2.64) | (-1.84) | (-1.64) | (-0.57) | (0.33) | (1.44) | (3.17) | (11.21) | (11.42) |
| HRP | -0.21 | -0.20 | -0.18 | -0.12 | -0.09 | 0.00 | 0.01 | 0.07 | 0.31 | 0.91 | 1.12 |
| | (-1.38) | (-1.35) | (-1.45) | (-0.94) | (-0.72) | (-0.02) | (0.11) | (0.63) | (2.55) | (6.67) | (9.48) |

## Table A3: Long-short option returns after excluding pharmaceutical stocks

This table shows alphas of option strategies after regressing ZHCT anomaly returns on option risk factors by ZHCT and TW. Column 1 reports the baseline anomaly mean returns from Table 2. Column 2 reports mean returns after *excluding* stocks in the pharmaceutical industry (FF49 code: 13) from the option sample. Column 3 reports alphas when regressing anomaly returns (constructed without pharmaceutical options) on TW+ZHCT risk factors (also constructed without pharmaceuticals). Option returns are from the perspective of an option writer under a daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percentage. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Base | w/o Drugs | w/o Drugs<br>TW+ZHCT |
| CH | 0.80 | 0.10 | 0.22 |
| | (7.17) | (1.00) | (1.98) |
| CFV | 0.64 | 0.47 | -0.15 |
| | (5.57) | (4.01) | (-1.50) |
| DISP | 0.31 | 0.14 | 0.00 |
| | (4.36) | (1.85) | (-0.04) |
| ISSUE_1Y | 0.41 | 0.05 | 0.03 |
| | (4.02) | (0.53) | (0.46) |
| ISSUE_5Y | 0.57 | 0.21 | 0.03 |
| | (5.96) | (2.82) | (0.34) |
| TEF | 0.53 | -0.02 | 0.00 |
| | (4.99) | (-0.26) | (0.02) |
| -PM | 0.87 | 0.31 | 0.01 |
| | (8.35) | (3.39) | (0.10) |
| -PRICE | 1.01 | 0.69 | 0.07 |
| | (7.01) | (4.76) | (0.88) |
| -PROFIT | 0.77 | 0.13 | 0.00 |
| | (7.79) | (1.57) | (-0.02) |
| -ZS | 0.23 | 0.35 | -0.01 |
| | (2.36) | (3.24) | (-0.05) |

## Table A4: Put options: long-short returns after adjustment for $f^{\text{PHARMA}}$

This table shows mean returns and alphas of *put* option strategies after regressing ZHCT anomaly returns on the pharmaceutical option factor, $f^{\text{PHARMA}}$, and industry-demeaned ZHCT and TW factors, denoted by "*". $f^{\text{PHARMA}}$ invests long in options on pharmaceuticals and is short in options on all other stocks. Option returns are from the perspective of an option writer under an initial and daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percent. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* $+f^{\text{PHARMA}}$ |
| CH | 0.63 | 0.14 | 0.50 | 0.08 |
| | (7.35) | (1.92) | (3.88) | (0.85) |
| CFV | 0.53 | 0.54 | -0.07 | -0.07 |
| | (6.85) | (4.62) | (-0.66) | (-0.70) |
| DISP | 0.31 | 0.30 | -0.02 | -0.01 |
| | (6.00) | (4.90) | (-0.22) | (-0.12) |
| ISSUE_1Y | 0.33 | 0.09 | 0.21 | 0.01 |
| | (3.77) | (1.28) | (2.08) | (0.10) |
| ISSUE_5Y | 0.44 | 0.22 | 0.35 | 0.16 |
| | (6.28) | (2.66) | (3.58) | (1.80) |
| TEF | 0.48 | 0.11 | 0.30 | 0.00 |
| | (6.08) | (1.34) | (2.67) | (-0.02) |
| -PM | 0.74 | 0.32 | 0.41 | 0.06 |
| | (9.86) | (3.80) | (2.98) | (0.55) |
| -PRICE | 0.71 | 0.62 | 0.03 | -0.02 |
| | (6.88) | (3.79) | (0.27) | (-0.18) |
| -PROFIT | 0.68 | 0.25 | 0.25 | -0.11 |
| | (9.33) | (3.27) | (2.49) | (-1.44) |
| -ZS | 0.21 | 0.20 | 0.05 | 0.00 |
| | (2.92) | (2.76) | (0.33) | (0.04) |

## Table A5: Initial hedge: long-short returns after adjustment for $f^{\text{PHARMA}}$

This table shows mean returns and alphas of *put* option strategies after regressing ZHCT anomaly returns on the pharmaceutical option factor, $f^{\text{PHARMA}}$, and industry-demeaned ZHCT and TW factors, denoted by "*". $f^{\text{PHARMA}}$ invests long in options on pharmaceuticals and is short in options on all other stocks. Option returns are from the perspective of an option writer under an *initial* delta-hedging schedule, see Equation (1). All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percent. A minus sign indicates that some strategies are based on 1-minus-10 decile portfolios instead. The sorting characteristics are detailed in Internet Appendix B. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* $+f^{\text{PHARMA}}$ |
| CH | 0.80 | 0.08 | 0.98 | 0.35 |
| | (4.15) | (0.68) | (4.69) | (2.02) |
| CFV | 0.02 | 0.24 | -0.58 | -0.44 |
| | (0.14) | (1.66) | (-2.47) | (-1.79) |
| DISP | 0.00 | 0.01 | 0.05 | 0.04 |
| | (0.01) | (0.09) | (0.35) | (0.27) |
| ISSUE_1Y | 0.30 | 0.13 | 0.42 | 0.28 |
| | (2.03) | (1.10) | (3.05) | (2.13) |
| ISSUE_5Y | 0.42 | 0.25 | 0.63 | 0.47 |
| | (2.76) | (1.56) | (2.16) | (1.66) |
| TEF | 0.44 | -0.02 | 0.61 | 0.21 |
| | (2.76) | (-0.22) | (3.69) | (1.41) |
| -PM | 0.43 | 0.06 | 0.61 | 0.28 |
| | (2.83) | (0.49) | (3.98) | (1.91) |
| -PRICE | 0.62 | 0.88 | 0.18 | 0.32 |
| | (3.16) | (3.73) | (1.14) | (1.50) |
| -PROFIT | 0.53 | -0.04 | 0.63 | 0.10 |
| | (3.11) | (-0.32) | (4.15) | (0.96) |
| -ZS | -0.18 | 0.15 | -0.34 | -0.08 |
| | (-1.37) | (1.06) | (-1.68) | (-0.40) |

# B Details on variable construction and definitions

## B.1 Option anomaly characteristics in ZHCT

1. CH: The cash-to-assets ratio defined as corporate cash holdings over total assets following (Palazzo, 2012). The data source is Jensen et al. (2023) (JKP) (item: cash_at).

2. CFV: The cash flow variance following Haugen and Baker (1996) is defined as the variance of the monthly ratio of cash flow to the market value of equity computed over the last 60 months. Cash flow is net income plus depreciation and amortization. The data source is Chen and Zimmermann (2022) (CZ) (item: VarCF).

3. DISP: Analyst earnings forecast dispersion computed as the standard deviation of analysts' annual earnings-per-share forecasts over the mean earnings estimate (Diether et al., 2002). The data source is CZ (item: ForecastDispersion).

4. ISSUE_1Y: One-year new share issues computed as the one-year growth of the number of shares outstanding (Pontiff & Woodgate, 2008). The data source is JKP (item: chcsho_12m).

5. ISSUE_5Y: Five-year new share issues computed as the five-year growth of the number of shares outstanding (Daniel & Titman, 2006). The data source is CZ (item: ShareIss5Y)

6. TEF: Total external financing defined as the sum of net share (equity issuance minus buybacks) and net debt issuance (debt issuance minus debt reduction) as in Bradshaw et al. (2006). Scaled by the firm´s total assets. The data source is JKP (item: netis_at).

7. PM: Profit margin folowing Soliman (2008) and defined as EBIT over total sales. The data source is JKP (item: ebit_at).

8. PRICE: The underlying stock's close price at the formation date of the option investment. The data is from CRSP.

9. Operating profitability: The operating profits-to-book equity ratio as in Fama and French (2015) (EBITDA minus interest expenses over book equity). The data source is JKP (item: ope_be).

10. ZS: The Altman z-score as defined in (Dichev, 1998):

    1.2 $\times$ (working capital / total assets) + 1.4 $\times$ (retained earnings / total assets) + 3.3 $\times$ (EBIT / total assets) + 0.6 $\times$ (equity market value / book value of total liabilities) + (sales / assets).

    The data source is JKP (item: z_score).

### B.2 Option risk factors

1. IVOL: The idiosyncratic volatility of the underlying relative to the Fama and French (1993) 3-factor model over the month before portfolio formation (Cao & Han, 2013; Zhan et al., 2022).

2. AMIHUD: The underlying stock's Amihud (2002) illiquidity measure computed using daily return and volume data during the one month before portfolio formation (Zhan et al., 2022).

3. HC: The delta hedging costs as in Tian and Wu (2023). Specifically, HC for stock $i$ at time $t$ is given by
$$\mathrm{HC}_{i,t} = \sigma_{t,i}\sqrt{(1-\rho_{t,i}^2)/\mathrm{DV}_{t,i}},$$
where $\sigma$ denotes the stock's historical return volatility estimator, $\rho$ the return correlation of the stock with the aggregate market portfolio, and DV denotes the stock's average dollar trading volume (in thousands). HC is estimated with daily returns and trading volumes over the past quarter.

4. VR: The volatility risk measure as in Tian and Wu (2023). VR is the standard deviation of daily changes of the stock $i$'s one-month at-the-money option implied volatility over the past month $t$.

5. JR: The (historical) jump risk as in Tian and Wu (2023). It is the product of the underlying stock's excess kurtosis and historical return volatility over the previous month.

6. VRP: The option implied volatility risk premium as in Goyal and Saretto (2009). Specifically, VRP is computed as the difference between at-the-money implied volatility (IV) and historical volatility (HV). IV is the average of at-the-money call and put one-month implied volatilities. HV is estimated using daily stock return data over the prior twelve months. (VRP is the -VOL_deviation measure in Zhan et al. (2022).)

7. HRP: The historical option risk premium computed as the average return on at-the-money options on the same stock over the past 12 months, excluding the most recent month. HRP is equivalent to the option momentum signal as Heston et al. (2023). The construction follows Käfer, Moerke, and Wiest (2025). It relies on month-end to month-end option returns (either initially or daily delta-hedged), using option return observations obtained after applying the data filters described in the main paper.

### B.3 Growth option characteristics

1. GO: The growth option variable, as in Andreou et al. (2024), is defined as the percentage of firm market value (V) arising from future-oriented growth opportunities (PVGO). V is the market capitalization (JKP: me) plus the total liabilities (Compu-

stat: lt). $\text{PVGO}_t$ is computed as $\text{V}_t - \frac{\text{CF}_t}{\text{WACC}_t}$, where CF is net operating cash flow from operating activities (oancf) plus interest and related expenses (xint) minus depreciation and amortization (dpc), and WACC is the cost of equity estimated using the market model and assuming that all firms have a beta of one. The market risk premium is given as the 60-month average of the return on the S&P500 minus the one-month T-bill yield (but no less than 4.5% in expectation). The cost of debt is assumed to be 4% below the cost of equity. I estimate effective tax rates by dividing income taxes (from Compustat: txt) by pretax income (from Compustat: pi). I use the SIC3 industry average if not available.

2. CFP: The cash-flow-to-price ratio is defined as net cash flow from operating activities over the firm's market capitalization (JKP item: ocf_me) (Desai, Rajgopal, & Venkatachalam, 2004).

3. MABA: The ratio of market value to book value of firm assets (JKP item: assets). Market value of assets is the book value of assets plus market capitalization (JKP item: me) minus book value of equity (JKP item: book_equity).

4. RD_AT: The ratio of R&D expenses to total assets (JKP item: rd_at).

5. RD_SALES: R&D intensity defined as R&D expenses scales by revenues (Chan, Lakonishok, & Sougiannis, 2001) (JKP item: rd_sale).

### B.4 Lottery features

1. $\mathbb{E}$[ISKEW]: The expected idiosyncratic skewness following Boyer et al. (2010). Specifically, this measure estimates a firm's idiosyncratic volatility, using Fama-French three-factor residuals, over the subsequent five-year period. To do so, I follow Boyer et al. (2010) in regressing an idiosyncratic volatility (ISKEW) estimate from $t$ to $t+T$ ($T = 60$ months) on firm-level information available at time $t-T$. I require at least 1,000 daily return (residual) observations to estimate skewness. In particular, I regress $\text{ISKEW}_{t,t+T}$ on lagged idiosyncratic skewness ($\text{ISKEW}_{t-T,t}$) and volatility ($\text{IVOL}_{t-T,t}$ as well as several controls. These controls include the stock momentum return over the months $t-T-12$ through $t-T-1$, the share turnover in month $t-T$, a dummy variable for small and medium-sized firms (based on market cap in $t-T$), as well as a dummy for firms trading on the NASDAQ exchange. I do not include industry dummies as this would dilute the difference in expected skewness between pharmaceuticals and other firms in the main paper.
I estimate regression coefficients by performing a cross-sectional regression each month. I then use the coefficient estimates and stock-level information available at the end of month $t+T$ (lagged skewness, volatility, and controls) to compute the expectation of idiosyncratic skewness over the next five years.
I use the whole CRSP-Compustat universe of common stocks on the NYSE, AMEX, and NASDAQ to estimate regression coefficients for predicting skewness out of sample.

2. JACKPOT: The underlying stock's jackpot probability following Conrad et al. (2014). This measure estimates the likelihood of a firm achieving a jackpot return of more than 100% over the next twelve months. To obtain model parameters, I follow Conrad et al. (2014) in estimating a baseline logit model, where I regress a dummy variable equal to one if the annual stock return is greater than 100% on various stock-level characteristics known at the beginning of the one-year period. These characteristics are the prior one-year return, realized volatility and skewness over the previous three months, detrended share turnover (turnover computed over six months minus the prior 18-month rolling average of share turnover), log market capitalization, firm age, gross gross property plant and equipment over total assets, and sales growth over the prior year. Accounting variables are lagged by four months following JKP.

   The logit model is estimated once a year in June (the jackpot indicator for the 12-month period from $t$ to $t + 12$ is regressed on characteristics known at $t$) using an expanding window of all previously available data. I then use the most recent model coefficient estimates with current firm characteristics to predict the jackpot probability, JACKPOT. Thereby, the jackpot prediction is out-of-sample and free of any look-ahead bias.

   I use the full CRSP-Compustat universe of common stocks on the NYSE, AMEX, and NASDAQ, starting in 1951, to estimate the coefficients of the logit model.

3. MAXRET: The maximum daily return of the underlying stock over the previous month (Bali et al., 2011). The measure is based on daily CRSP returns.

## C Additional stock-level characteristics

### C.1 Characteristics overview

This list summarizes stock factor characteristics from Jensen et al. (2023) (JKP). Details on the construction are available on the authors' website: `https://jkpfactors.com/factor-returns`. JKP sort characteristics into clusters using the hierarchical agglomerative clustering by Murtagh and Legendre (2014). To avoid duplication (such as with the ZHCT sorting characteristics), I exclude the following 13 characteristics as they appear in other analyses throughout this paper: cash_at, chcsho_12m, netis_at, ebit_sale, ope_be, z_score, ivol_ff3_21d, rd_sale, prc, ocfq_saleq_std, ami_126d, rmax1_21d, ocf_me.

| **Description** | **Variable** | **Reference paper** |
|---|---|---|
| 1: ACCRUALS | | |
| Change in current operating working capital | cowc_gr1a | Richardson, Sloan, Soliman, and Tuna (2005) |
| Operating accruals | oaccruals_at | Sloan (1996) |
| Percent operating accruals | oaccruals_ni | Hafzalla, Lundholm, and Van Winkle (2011) |
| Years 16-20 lagged returns, nonannual | seas_16_20na | Heston and Sadka (2008) |
| Total accruals | taccruals_at | Richardson et al. (2005) |
| Percent total accruals | taccruals_ni | Hafzalla et al. (2011) |
| 2: DEBT ISSUANCE | | |
| Abnormal corporate investment | capex_abn | Titman, Wei, and Xie (2004) |
| Growth in book debt (3 years) | debt_gr3 | Lyandres, Sun, and Zhang (2008) |
| Change in financial liabilities | fnl_gr1a | Richardson et al. (2005) |
| Change in noncurrent operating liabilities | ncol_gr1a | Richardson et al. (2005) |
| Change in net financial assets | nfna_gr1a | Richardson et al. (2005) |
| Earnings persistence | ni_ar1 | Francis, Lafond, Olsson, and Schipper (2004) |
| Net operating assets | noa_at | Hirshleifer, Hou, Teoh, and Zhang (2004) |
| 3: INVESTMENT | | |
| Liquidity of book assets | aliq_at | Ortiz-Molina and Phillips (2014) |
| Asset Growth | at_gr1 | Cooper, Gulen, and Schill (2008) |
| Change in common equity | be_gr1a | Richardson et al. (2005) |
| CAPEX growth (1 year) | capx_gr1 | Xie (2001) |
| CAPEX growth (2 years) | capx_gr2 | Anderson and Garcia-Feijoo (2006) |
| CAPEX growth (3 years) | capx_gr3 | Anderson and Garcia-Feijoo (2006) |
| Change in current operating assets | coa_gr1a | Richardson et al. (2005) |
| Change in current operating liabilities | col_gr1a | Richardson et al. (2005) |
| Hiring rate | emp_gr1 | Belo, Lin, and Bazdresch (2014) |
| Inventory growth | inv_gr1 | Belo and Lin (2012) |
| Inventory change | inv_gr1a | J. K. Thomas and Zhang (2002) |

*(continued)*

| Description | Variable | Reference paper |
|---|---|---|
| Change in long-term net operating assets | lnoa_gr1a | Fairfield, Whisenant, and Yohn (2003) |
| Mispricing factor: Management | mispricing_mgmt | Stambaugh and Yuan (2017) |
| Change in noncurrent operating assets | ncoa_gr1a | Richardson et al. (2005) |
| Change in net noncurrent operating assets | nncoa_gr1a | Richardson et al. (2005) |
| Change in net operating assets | noa_gr1a | Hirshleifer et al. (2004) |
| Change PPE and Inventory | ppeinv_gr1a | Lyandres et al. (2008) |
| Long-term reversal | ret_60_12 | De Bondt and Thaler (1985) |
| Sales growth (1 year) | sale_gr1 | Lakonishok, Shleifer, and Vishny (1994) |
| Sales growth (3 years) | sale_gr3 | Lakonishok et al. (1994) |
| Sales growth (1 quarter) | saleq_gr1 | |
| Years 2-5 lagged returns, nonannual | seas_2_5na | Heston and Sadka (2008) |
| 4: LOW LEVERAGE | | |
| Firm age | age | Jiang, Lee, and Zhang (2005) |
| Liquidity of market assets | aliq_mat | Ortiz-Molina and Phillips (2014) |
| Book leverage | at_be | Fama and French (1992) |
| The high-low bid-ask spread | bidaskhl_21d | Corwin and Schultz (2012) |
| Net debt-to-price | netdebt_me | Penman, Richardson, and Tuna (2007) |
| Earnings volatility | ni_ivol | Francis et al. (2004) |
| R&D capital-to-book assets | rd5_at | Li (2011) |
| Asset tangibility | tangibility | Hahn and Lee (2009) |
| 5: LOW RISK | | |
| Market Beta | beta_60m | Fama and MacBeth (1973) |
| Dimson beta | beta_dimson_21d | Dimson (1979) |
| Frazzini-Pedersen market beta | betabab_1260d | Frazzini and Pedersen (2014) |
| Downside beta | betadown_252d | Ang, Chen, and Xing (2006) |
| Earnings variability | earnings_variability | Francis et al. (2004) |
| Idiosyncratic volatility from the CAPM (21 days) | ivol_capm_21d | |
| Idiosyncratic volatility from the CAPM (252 days) | ivol_capm_252d | Ali, Hwang, and Trombley (2003) |
| Idiosyncratic volatility from the qfactor model | ivol_hxz4_21d | |
| Highest 5 days of return | rmax5_21d | Bali, Brown, and Tang (2017) |
| Return volatility | rvol_21d | Ang, Hodrick, Xing, and Zhang (2006) |
| Years 6-10 lagged returns, nonannual | seas_6_10na | Heston and Sadka (2008) |
| Share turnover | turnover_126d | Datar, Naik, and Radcliffe (1998) |
| Number of zero trades with turnover as tiebreaker (1 month) | zero_trades_126d | Liu (2006) |
| Number of zero trades with turnover as tiebreaker (6 months) | zero_trades_21d | Liu (2006) |

*(continued)*

| Description | Variable | Reference paper |
|---|---|---|
| Number of zero trades with turnover as tiebreaker (12 months) | zero_trades_252d | Liu (2006) |
| 6: MOMENTUM | | |
| Current price to high price over last year | prc_highprc_252d | George and Hwang (2004) |
| Residual momentum t-6 to t-1 | resff3_12_1 | Blitz, Huij, and Martens (2011) |
| Residual momentum t-12 to t-1 | resff3_6_1 | Blitz et al. (2011) |
| Price momentum t-3 to t-1 | ret_12_1 | Jegadeesh and Titman (1993) |
| Price momentum t-6 to t-1 | ret_3_1 | Jegadeesh and Titman (1993) |
| Price momentum t-9 to t-1 | ret_6_1 | Jegadeesh and Titman (1993) |
| Price momentum t-12 to t-1 | ret_9_1 | Jegadeesh and Titman (1993) |
| Year 1-lagged return, nonannual | seas_1_1na | Heston and Sadka (2008) |
| 7: PROFIT GROWTH | | |
| Change sales minus change Inventory | dsale_dinv | Abarbanell and Bushee (1998) |
| Change sales minus change receivables | dsale_drec | Abarbanell and Bushee (1998) |
| Change sales minus change SG&A | dsale_dsga | Abarbanell and Bushee (1998) |
| Change in quarterly return on assets | niq_at_chg1 | |
| Change in quarterly return on equity | niq_be_chg1 | |
| Standardized earnings surprise | niq_su | Foster, Olsen, and Shevlin (1984) |
| Change in operating cash flow to assets | ocf_at_chg1 | Bouchaud, Krueger, Landier, and Thesmar (2019) |
| Price momentum t-12 to t-7 | ret_12_7 | Novy-Marx (2012) |
| Labor force efficiency | sale_emp_gr1 | Abarbanell and Bushee (1998) |
| Standardized Revenue surprise | saleq_su | Jegadeesh and Livnat (2006) |
| Year 1-lagged return, annual | seas_1_1an | Heston and Sadka (2008) |
| Tax expense surprise | tax_gr1a | J. Thomas and Zhang (2011) |
| 8: PROFITABILITY | | |
| Coefficient of variation for dollar trading volume | dolvol_var_126d | Chordia, Subrahmanyam, and Anshuman (2001) |
| Return on net operating assets | ebit_bev | Soliman (2008) |
| Pitroski F-score | f_score | Piotroski (2000) |
| Return on equity | ni_be | Haugen and Baker (1996) |
| Quarterly return on equity | niq_be | Hou, Xue, and Zhang (2015) |
| Ohlson O-score | o_score | Dichev (1998) |
| Operating cash flow to assets | ocf_at | Bouchaud et al. (2019) |
| Operating profits-to-lagged book equity | ope_bel1 | |
| Coefficient of variation for share turnover | turnover_var_126d | Chordia et al. (2001) |
| 9: QUALITY | | |
| Capital turnover | at_turnover | Haugen and Baker (1996) |
| Cash-based operating profits-tobook assets | cop_at | |

*(continued)*

| Description | Variable | Reference paper |
|---|---|---|
| Cash-based operating profits-tolagged book assets | cop_atl1 | Ball, Gerakos, Linnainmaa, and Nikolaev (2016) |
| Change gross margin minus change sales | dgp_dsale | Abarbanell and Bushee (1998) |
| Gross profits-to-assets | gp_at | Novy-Marx (2013) |
| Gross profits-to-lagged assets | gp_atl1 | |
| Mispricing factor: Performance | mispricing_perf | Stambaugh and Yuan (2017) |
| Number of consecutive quarters with earnings increases | ni_inc8q | Barth, Elliott, and Finn (1999) |
| Quarterly return on assets | niq_at | Balakrishnan, Bartov, and Faurel (2010) |
| Operating profits-to-book assets | op_at | |
| Operating profits-to-lagged book assets | op_atl1 | Ball et al. (2016) |
| Operating leverage | opex_at | Novy-Marx (2011) |
| Quality minus Junk: Composite | qmj | C. S. Asness, Frazzini, and Pedersen (2019) |
| Quality minus Junk: Growth | qmj_growth | C. S. Asness et al. (2019) |
| Quality minus Junk: Profitability | qmj_prof | C. S. Asness et al. (2019) |
| Quality minus Junk: Safety | qmj_safety | C. S. Asness et al. (2019) |
| Assets turnover | sale_bev | Soliman (2008) |
| 10: SEASONALITY | | |
| Market correlation | corr_1260d | C. Asness, Frazzini, Gormsen, and Pedersen (2020) |
| Coskewness | coskew_21d | Harvey and Siddique (2000) |
| Net debt issuance | dbnetis_at | Bradshaw et al. (2006) |
| Kaplan-Zingales index | kz_index | Lamont, Polk, and Saaa-Requejo (2001) |
| Change in long-term investments | lti_gr1a | Richardson et al. (2005) |
| Taxable income-to-book income | pi_nix | Lev and Nissim (2004) |
| Years 11-15 lagged returns, annual | seas_11_15an | Heston and Sadka (2008) |
| Years 11-15 lagged returns, nonannual | seas_11_15na | Heston and Sadka (2008) |
| Years 16-20 lagged returns, annual | seas_16_20an | Heston and Sadka (2008) |
| Years 2-5 lagged returns, annual | seas_2_5an | Heston and Sadka (2008) |
| Years 6-10 lagged returns, annual | seas_6_10an | Heston and Sadka (2008) |
| Change in short-term investments | sti_gr1a | Richardson et al. (2005) |
| 11: SHORT-TERM REVERSAL | | |
| Idiosyncratic skewness from the CAPM | iskew_capm_21d | |
| Idiosyncratic skewness from the Fama-French 3-factor model | iskew_ff3_21d | Bali, Engle, and Murray (2016) |
| Idiosyncratic skewness from the qfactor model | iskew_hxz4_21d | |
| Short-term reversal | ret_1_0 | Jegadeesh (1990) |
| Highest 5 days of return scaled by volatility | rmax5_rvol_21d | C. Asness et al. (2020) |

*(continued)*

| Description | Variable | Reference paper |
|---|---|---|
| Total skewness | rskew_21d | Bali et al. (2016) |
| 12: SIZE | | |
| Dollar trading volume | dolvol_126d | Brennan, Chordia, and Subrahmanyam (1998) |
| Market Equity | market_equity | Banz (1981) |
| R&D-to-market | rd_me | Chan et al. (2001) |
| 13: VALUE | | |
| Assets-to-market | at_me | Fama and French (1992) |
| Book-to-market equity | be_me | Rosenberg, Reid, and Lanstein (1985) |
| Book-to-market enterprise value | bev_mev | Penman et al. (2007) |
| Debt-to-market | debt_me | Bhandari (1988) |
| Dividend yield | div12m_me | Litzenberger and Ramaswamy (1979) |
| EBITDA-to-market enterprise value | ebitda_mev | Loughran and Wellman (2011) |
| Equity duration | eq_dur | Dechow, Sloan, and Soliman (2004) |
| Net equity issuance | eqnetis_at | Bradshaw et al. (2006) |
| Equity net payout | eqnpo_12m | Daniel and Titman (2006) |
| Net payout yield | eqnpo_me | Boudoukh, Michaely, Richardson, and Roberts (2007) |
| Payout yield | eqpo_me | Boudoukh et al. (2007) |
| Free cash flow-to-price | fcf_me | Lakonishok et al. (1994) |
| Intrinsic value-to-market | ival_me | Frankel and Lee (1998) |
| Earnings-to-price | ni_me | Basu (1983) |
| Sales-to-market | sale_me | Barbee Jr, Mukherji, and Raines (1996) |

### C.2 Additional anomaly returns

The following table lists mean returns and alphas of option strategies using the JKP stock factor characteristics listed in Internet Appendix C.1. I regress anomaly returns on the pharmaceutical option factor, $f^{\text{PHARMA}}$, industry-demeaned ZHCT and TW factors (denoted by "*"), and industry-*unadjusted* ZHCT and TW factors. $f^{\text{PHARMA}}$ invests long in pharmaceutical options and is short in options on all other stocks. Option returns are from the perspective of an option writer under a daily delta-hedging schedule. All strategies are equal-weighted 10-minus-1 decile portfolios, with average returns in percent. The last column (PHARMA impact) denotes the impact of controlling for the exposure to pharmaceutical options. "n.a." indicates that the anomaly mean return did not exhibit an absolute $t$-stat above 3 to begin with. "−" indicates no considerable impact of controlling for $f^{\text{PHARMA}}$ with the absolute $t$-stat in column 2 remaining above 3 or the industry-demeaned model, TW*+ZHCT*, also reducing the absolute $t$-stat to below 3. "✓" indicates that $f^{\text{PHARMA}}$ (alone or jointly with TW*+ZHCT*) reduces the absolute anomaly $t$-stat below 3, whereas TW*+ZHCT* on its own does not. "✓✓" indicates that $f^{\text{PHARMA}}$ (alone or jointly with TW*+ZHCT*) reduces the absolute anomaly $t$-stat below 3, whereas the full industry-undadjusted TW+ZHCT factors do not. $t$-stats based on Newey and West (1987) adjusted standard errors with 4 lags are in parentheses. The sample period is 02-1996 to 12-2022.

| Char. | (1) Mean | (2) $f^{\text{PHARMA}}$ | (3) TW*+ZHCT* | (4) TW*+ZHCT* $+f^{\text{PHARMA}}$ | (5) TW+ZHCT full | PHARMA impact |
|---|---|---|---|---|---|---|
| 1: ACCRUALS | | | | | | |
| cowc_gr1a | -0.23 | -0.20 | -0.16 | -0.15 | -0.22 | – |
| | (-4.34) | (-3.26) | (-1.67) | (-1.59) | (-2.04) | |
| oaccruals_at | -0.32 | -0.17 | -0.13 | -0.07 | -0.20 | – |
| | (-5.56) | (-2.20) | (-1.28) | (-0.69) | (-1.82) | |
| oaccruals_ni | -0.01 | -0.12 | 0.02 | -0.06 | -0.06 | n.a. |
| | (-0.19) | (-2.03) | (0.26) | (-0.72) | (-0.70) | |
| seas_16_20na | 0.08 | 0.14 | 0.30 | 0.33 | 0.27 | n.a. |
| | (1.13) | (1.53) | (3.65) | (3.23) | (2.80) | |
| taccruals_at | 0.00 | 0.01 | 0.11 | 0.10 | 0.02 | n.a. |
| | (0.09) | (0.11) | (0.97) | (0.83) | (0.20) | |
| taccruals_ni | 0.19 | 0.06 | 0.30 | 0.23 | 0.20 | ✓ |
| | (4.24) | (1.25) | (3.84) | (2.66) | (2.24) | |
| 2: DEBT ISSUANCE | | | | | | |
| capex_abn | -0.20 | -0.11 | -0.06 | 0.00 | -0.02 | – |
| | (-3.76) | (-1.71) | (-0.66) | (0.02) | (-0.18) | |
| debt_gr3 | -0.13 | -0.07 | -0.31 | -0.26 | -0.22 | n.a. |
| | (-2.09) | (-0.81) | (-3.19) | (-2.82) | (-2.11) | |
| fnl_gr1a | -0.20 | -0.22 | -0.16 | -0.15 | -0.14 | – |
| | (-4.18) | (-3.71) | (-1.94) | (-1.84) | (-1.67) | |
| ncol_gr1a | -0.10 | -0.13 | -0.06 | -0.08 | -0.06 | n.a. |
| | (-2.22) | (-2.86) | (-0.94) | (-1.24) | (-0.80) | |
| nfna_gr1a | 0.26 | 0.19 | 0.24 | 0.20 | 0.20 | – |
| | (4.85) | (2.85) | (2.49) | (1.86) | (1.98) | |
| ni_ar1 | -0.10 | -0.08 | -0.09 | -0.08 | -0.12 | n.a. |
| | (-2.37) | (-1.53) | (-1.29) | (-1.08) | (-1.37) | |
| noa_at | -0.76 | -0.19 | -0.70 | -0.31 | -0.53 | ✓✓ |
| | (-8.74) | (-2.48) | (-6.07) | (-2.82) | (-4.02) | |
| 3: INVESTMENT | | | | | | |
| aliq_at | 0.21 | -0.10 | 0.21 | 0.08 | 0.12 | n.a. |
| | (1.92) | (-1.02) | (2.03) | (0.71) | (1.07) | |
| at_gr1 | -0.23 | -0.16 | 0.06 | 0.15 | 0.04 | n.a. |
| | (-2.36) | (-1.65) | (0.53) | (1.42) | (0.33) | |
| be_gr1a | -0.08 | -0.11 | 0.10 | 0.11 | 0.06 | n.a. |
| | (-0.87) | (-1.22) | (0.81) | (0.99) | (0.51) | |
| capx_gr1 | -0.11 | -0.17 | 0.11 | 0.10 | 0.05 | n.a. |
| | (-1.17) | (-2.07) | (1.03) | (0.97) | (0.45) | |
| capx_gr2 | -0.16 | -0.20 | 0.15 | 0.13 | 0.10 | n.a. |
| | (-1.93) | (-2.32) | (1.70) | (1.34) | (0.98) | |
| capx_gr3 | -0.23 | -0.26 | -0.12 | -0.12 | -0.14 | – |
| | (-3.04) | (-3.16) | (-1.06) | (-1.05) | (-1.24) | |
| coa_gr1a | -0.33 | -0.34 | -0.15 | -0.14 | -0.26 | – |
| | (-5.03) | (-4.69) | (-1.88) | (-1.72) | (-3.28) | |
| col_gr1a | -0.23 | -0.20 | 0.01 | 0.06 | -0.05 | n.a. |
| | (-2.94) | (-2.74) | (0.14) | (0.67) | (-0.58) | |
| emp_gr1 | -0.15 | -0.29 | -0.07 | -0.11 | -0.11 | n.a. |
| | (-1.66) | (-3.37) | (-0.66) | (-0.89) | (-0.88) | |
| inv_gr1 | -0.24 | -0.36 | -0.25 | -0.33 | -0.28 | – |
| | (-4.10) | (-5.85) | (-2.99) | (-3.45) | (-2.91) | |

*(continued)*

| | (1) | (2) | (3) | (4) | (5) | |
|---|---|---|---|---|---|---|
| Char. | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* $+f^{\text{PHARMA}}$ | TW+ZHCT full | PHARMA impact |
| inv_gr1a | -0.22 | -0.28 | -0.10 | -0.15 | -0.17 | – |
| | (-3.78) | (-4.27) | (-1.30) | (-1.73) | (-1.99) | |
| lnoa_gr1a | -0.39 | -0.33 | -0.24 | -0.21 | -0.29 | ✓✓ |
| | (-6.59) | (-6.19) | (-3.74) | (-2.85) | (-3.75) | |
| mispricing_mgmt | 0.16 | 0.12 | 0.14 | 0.06 | 0.21 | n.a. |
| | (1.98) | (1.54) | (1.54) | (0.75) | (2.34) | |
| ncoa_gr1a | -0.30 | -0.26 | -0.16 | -0.10 | -0.21 | – |
| | (-4.29) | (-3.84) | (-1.96) | (-1.26) | (-2.56) | |
| nncoa_gr1a | -0.39 | -0.30 | -0.27 | -0.18 | -0.30 | ✓✓ |
| | (-5.58) | (-4.45) | (-3.78) | (-2.53) | (-3.69) | |
| noa_gr1a | -0.42 | -0.24 | -0.35 | -0.18 | -0.37 | ✓✓ |
| | (-5.65) | (-3.07) | (-3.40) | (-1.94) | (-3.52) | |
| ppeinv_gr1a | -0.33 | -0.28 | -0.17 | -0.10 | -0.22 | – |
| | (-4.30) | (-3.48) | (-1.97) | (-1.15) | (-2.26) | |
| ret_60_12 | -0.49 | -0.43 | -0.14 | -0.10 | -0.05 | – |
| | (-5.04) | (-4.08) | (-1.13) | (-0.75) | (-0.38) | |
| sale_gr1 | -0.21 | -0.19 | -0.04 | 0.01 | -0.11 | n.a. |
| | (-2.11) | (-2.31) | (-0.39) | (0.08) | (-0.98) | |
| sale_gr3 | -0.22 | -0.30 | -0.13 | -0.16 | -0.21 | – |
| | (-3.01) | (-3.60) | (-1.10) | (-1.37) | (-1.76) | |
| saleq_gr1 | -0.19 | -0.12 | 0.03 | 0.14 | 0.02 | n.a. |
| | (-2.06) | (-1.41) | (0.31) | (1.39) | (0.15) | |
| seas_2_5na | 0.00 | -0.21 | 0.08 | -0.02 | 0.06 | n.a. |
| | (0.05) | (-2.48) | (0.67) | (-0.16) | (0.39) | |
| 4: LOW LEVERAGE | | | | | | |
| age | -0.10 | 0.06 | 0.01 | 0.06 | 0.12 | n.a. |
| | (-1.06) | (0.61) | (0.11) | (0.55) | (1.24) | |
| aliq_mat | 0.04 | 0.19 | -0.08 | 0.01 | -0.08 | n.a. |
| | (0.45) | (1.97) | (-0.66) | (0.07) | (-0.68) | |
| at_be | -0.35 | 0.07 | -0.26 | -0.04 | -0.12 | – |
| | (-3.43) | (0.83) | (-1.80) | (-0.34) | (-0.95) | |
| bidaskhl_21d | 0.56 | 0.25 | 0.00 | -0.09 | -0.01 | – |
| | (4.31) | (1.87) | (0.01) | (-0.83) | (-0.08) | |
| netdebt_me | -0.50 | -0.10 | -0.53 | -0.29 | -0.35 | ✓ |
| | (-5.90) | (-1.13) | (-3.96) | (-2.23) | (-2.50) | |
| ni_ivol | 0.98 | 0.33 | 0.35 | 0.01 | 0.15 | – |
| | (8.57) | (3.21) | (2.89) | (0.07) | (1.22) | |
| rd5_at | 1.09 | 0.06 | 0.58 | -0.06 | 0.39 | ✓ |
| | (8.42) | (0.57) | (3.57) | (-0.37) | (2.37) | |
| tangibility | 0.44 | 0.00 | 0.31 | 0.04 | 0.21 | ✓ |
| | (6.13) | (-0.04) | (3.24) | (0.40) | (2.08) | |
| 5: LOW RISK | | | | | | |
| beta_60m | 0.10 | 0.09 | 0.08 | 0.15 | 0.13 | n.a. |
| | (1.14) | (0.82) | (0.71) | (1.39) | (1.23) | |
| beta_dimson_21d | -0.24 | -0.16 | 0.03 | 0.14 | 0.14 | n.a. |
| | (-2.54) | (-1.24) | (0.22) | (0.85) | (0.95) | |
| betabab_1260d | -0.21 | -0.12 | 0.01 | 0.13 | 0.20 | n.a. |
| | (-1.63) | (-0.82) | (0.04) | (0.84) | (1.28) | |

*(continued)*

| | (1) | (2) | (3) | (4) | (5) | |
|---|---|---|---|---|---|---|
| Char. | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* $+f^{\text{PHARMA}}$ | TW+ZHCT full | PHARMA impact |
| betadown_252d | -0.02 | 0.01 | 0.12 | 0.22 | 0.27 | n.a. |
| | (-0.12) | (0.09) | (0.77) | (1.36) | (1.58) | |
| earnings_variability | 0.36 | 0.24 | 0.12 | 0.10 | 0.12 | – |
| | (6.35) | (3.69) | (1.46) | (1.12) | (1.37) | |
| ivol_capm_21d | 0.82 | 0.53 | 0.17 | 0.08 | 0.04 | – |
| | (6.53) | (4.66) | (2.31) | (1.18) | (0.96) | |
| ivol_capm_252d | 0.87 | 0.50 | 0.38 | 0.24 | 0.28 | ✓ |
| | (6.29) | (3.50) | (3.73) | (2.36) | (2.75) | |
| ivol_hxz4_21d | 0.82 | 0.53 | 0.16 | 0.07 | 0.01 | – |
| | (6.97) | (4.86) | (2.71) | (1.20) | (0.30) | |
| rmax5_21d | 0.51 | 0.23 | 0.15 | 0.06 | 0.11 | – |
| | (3.89) | (1.97) | (1.55) | (0.59) | (1.34) | |
| rvol_21d | 0.67 | 0.45 | 0.14 | 0.11 | 0.05 | – |
| | (4.60) | (3.57) | (1.66) | (1.42) | (0.90) | |
| seas_6_10na | -0.14 | -0.15 | 0.01 | 0.04 | -0.02 | n.a. |
| | (-1.90) | (-1.72) | (0.06) | (0.43) | (-0.23) | |
| turnover_126d | 0.30 | 0.18 | -0.05 | -0.02 | 0.04 | n.a. |
| | (2.63) | (1.88) | (-0.51) | (-0.21) | (0.41) | |
| zero_trades_126d | -0.28 | -0.16 | 0.06 | 0.03 | -0.04 | n.a. |
| | (-2.43) | (-1.68) | (0.58) | (0.27) | (-0.38) | |
| zero_trades_21d | -0.45 | -0.30 | 0.02 | 0.00 | -0.03 | – |
| | (-3.58) | (-3.32) | (0.21) | (-0.01) | (-0.28) | |
| zero_trades_252d | -0.22 | -0.13 | 0.05 | -0.02 | -0.02 | n.a. |
| | (-1.97) | (-1.32) | (0.45) | (-0.16) | (-0.19) | |
| 6: MOMENTUM | | | | | | |
| prc_highprc_252d | -0.31 | -0.44 | 0.31 | 0.14 | 0.24 | n.a. |
| | (-2.04) | (-2.34) | (2.03) | (0.88) | (1.56) | |
| resff3_12_1 | -0.01 | -0.03 | 0.30 | 0.27 | 0.23 | n.a. |
| | (-0.20) | (-0.36) | (2.88) | (2.49) | (2.20) | |
| resff3_6_1 | 0.03 | -0.04 | 0.18 | 0.13 | 0.17 | n.a. |
| | (0.46) | (-0.57) | (2.03) | (1.39) | (1.93) | |
| ret_12_1 | 0.08 | -0.24 | 0.51 | 0.31 | 0.28 | n.a. |
| | (0.64) | (-1.64) | (3.42) | (1.96) | (1.75) | |
| ret_3_1 | 0.15 | -0.13 | 0.48 | 0.26 | 0.34 | n.a. |
| | (1.41) | (-1.17) | (3.44) | (1.86) | (2.45) | |
| ret_6_1 | 0.07 | -0.22 | 0.45 | 0.25 | 0.34 | n.a. |
| | (0.59) | (-1.32) | (2.90) | (1.52) | (2.22) | |
| ret_9_1 | 0.10 | -0.22 | 0.61 | 0.37 | 0.42 | n.a. |
| | (0.78) | (-1.25) | (3.87) | (2.26) | (2.57) | |
| seas_1_1na | 0.35 | -0.08 | 0.74 | 0.45 | 0.48 | n.a. |
| | (2.35) | (-0.48) | (3.73) | (2.05) | (2.20) | |
| 7: PROFIT GROWTH | | | | | | |
| dsale_dinv | 0.12 | 0.04 | 0.18 | 0.13 | 0.10 | n.a. |
| | (2.40) | (0.57) | (2.08) | (1.36) | (1.06) | |
| dsale_drec | 0.15 | 0.09 | 0.25 | 0.19 | 0.30 | n.a. |
| | (2.94) | (1.55) | (2.97) | (2.04) | (3.12) | |
| dsale_dsga | -0.20 | -0.17 | 0.12 | 0.14 | 0.09 | n.a. |
| | (-2.62) | (-2.12) | (1.04) | (1.19) | (0.87) | |

*(continued)*

| Char. | (1) Mean | (2) $f^{\text{PHARMA}}$ | (3) TW*+ZHCT* | (4) TW*+ZHCT* $+f^{\text{PHARMA}}$ | (5) TW+ZHCT full | PHARMA impact |
|---|---|---|---|---|---|---|
| niq_at_chg1 | 0.13 | 0.14 | 0.19 | 0.20 | 0.19 | n.a. |
| | (2.05) | (1.87) | (2.07) | (2.00) | (1.90) | |
| niq_be_chg1 | 0.06 | 0.10 | 0.27 | 0.28 | 0.20 | n.a. |
| | (0.93) | (1.41) | (2.61) | (2.63) | (2.01) | |
| niq_su | -0.08 | -0.07 | 0.08 | 0.07 | 0.04 | n.a. |
| | (-1.47) | (-1.13) | (0.93) | (0.80) | (0.39) | |
| ocf_at_chg1 | 0.07 | 0.14 | 0.13 | 0.19 | 0.18 | n.a. |
| | (1.22) | (1.98) | (1.27) | (1.78) | (1.65) | |
| ret_12_7 | 0.04 | 0.00 | 0.38 | 0.37 | 0.24 | n.a. |
| | (0.44) | (0.01) | (3.48) | (3.08) | (1.90) | |
| sale_emp_gr1 | -0.01 | -0.02 | 0.21 | 0.19 | 0.18 | n.a. |
| | (-0.22) | (-0.29) | (2.40) | (2.03) | (2.03) | |
| saleq_su | -0.13 | -0.18 | 0.04 | 0.03 | 0.01 | n.a. |
| | (-1.99) | (-2.74) | (0.57) | (0.35) | (0.13) | |
| seas_1_1an | 0.05 | 0.06 | 0.05 | 0.08 | 0.08 | n.a. |
| | (0.77) | (0.83) | (0.54) | (0.97) | (0.78) | |
| tax_gr1a | 0.00 | -0.04 | 0.10 | 0.08 | 0.08 | n.a. |
| | (-0.09) | (-0.70) | (1.29) | (0.97) | (1.01) | |
| 8: PROFITABILITY | | | | | | |
| dolvol_var_126d | 0.87 | 0.51 | 0.40 | 0.18 | 0.17 | ✓ |
| | (9.42) | (5.31) | (4.04) | (1.71) | (1.64) | |
| ebit_bev | -0.68 | -0.31 | -0.16 | 0.03 | -0.04 | – |
| | (-7.18) | (-2.75) | (-1.58) | (0.30) | (-0.37) | |
| f_score | -0.25 | 0.05 | 0.00 | 0.18 | 0.11 | – |
| | (-3.34) | (0.82) | (0.03) | (1.78) | (1.02) | |
| ni_be | -0.71 | -0.23 | -0.19 | 0.06 | -0.06 | – |
| | (-7.74) | (-2.04) | (-1.69) | (0.48) | (-0.54) | |
| niq_be | -0.67 | -0.21 | -0.15 | 0.09 | 0.00 | – |
| | (-7.07) | (-2.01) | (-1.32) | (0.78) | (-0.04) | |
| o_score | 0.92 | 0.39 | 0.28 | -0.03 | 0.06 | – |
| | (8.69) | (2.72) | (2.61) | (-0.29) | (0.53) | |
| ocf_at | -0.85 | -0.24 | -0.37 | -0.01 | -0.08 | ✓ |
| | (-8.12) | (-1.93) | (-3.51) | (-0.06) | (-0.79) | |
| ope_bel1 | -0.85 | -0.20 | -0.37 | 0.01 | -0.14 | ✓ |
| | (-8.35) | (-1.95) | (-3.33) | (0.08) | (-1.35) | |
| turnover_var_126d | 0.90 | 0.53 | 0.36 | 0.13 | 0.16 | ✓ |
| | (9.90) | (5.62) | (3.92) | (1.34) | (1.66) | |
| 9: QUALITY | | | | | | |
| at_turnover | -0.64 | -0.26 | -0.51 | -0.29 | -0.45 | ✓✓ |
| | (-7.28) | (-3.47) | (-4.22) | (-2.61) | (-4.28) | |
| cop_at | -0.43 | -0.32 | -0.04 | -0.01 | 0.11 | – |
| | (-4.17) | (-2.74) | (-0.31) | (-0.06) | (0.97) | |
| cop_atl1 | -0.42 | -0.32 | 0.10 | 0.14 | 0.23 | – |
| | (-4.03) | (-2.46) | (0.86) | (1.28) | (1.96) | |
| dgp_dsale | 0.00 | -0.11 | 0.18 | 0.09 | 0.03 | n.a. |
| | (-0.04) | (-1.62) | (1.91) | (0.95) | (0.34) | |
| gp_at | -0.82 | -0.31 | -0.49 | -0.18 | -0.36 | ✓✓ |
| | (-7.69) | (-3.49) | (-3.46) | (-1.40) | (-3.03) | |

*(continued)*

| Char. | (1) Mean | (2) $f^{\text{PHARMA}}$ | (3) TW*+ZHCT* | (4) TW*+ZHCT* $+f^{\text{PHARMA}}$ | (5) TW+ZHCT full | PHARMA impact |
|---|---|---|---|---|---|---|
| gp_atl1 | -0.89 | -0.36 | -0.44 | -0.08 | -0.29 | ✓ |
| | (-7.68) | (-4.08) | (-3.17) | (-0.69) | (-2.30) | |
| mispricing_perf | -0.84 | -0.40 | -0.13 | 0.13 | -0.10 | – |
| | (-7.28) | (-2.55) | (-0.97) | (1.03) | (-0.76) | |
| ni_inc8q | -0.15 | -0.09 | 0.04 | 0.08 | 0.00 | n.a. |
| | (-2.59) | (-1.07) | (0.48) | (0.86) | (0.06) | |
| niq_at | -0.89 | -0.32 | -0.37 | -0.05 | -0.18 | ✓ |
| | (-9.08) | (-2.60) | (-3.44) | (-0.56) | (-1.67) | |
| op_at | -0.70 | -0.45 | -0.12 | -0.03 | 0.00 | – |
| | (-6.27) | (-3.09) | (-1.05) | (-0.25) | (-0.04) | |
| op_atl1 | -0.72 | -0.45 | -0.16 | -0.03 | -0.04 | – |
| | (-6.95) | (-3.72) | (-1.40) | (-0.25) | (-0.37) | |
| opex_at | 0.03 | -0.17 | -0.16 | -0.29 | -0.32 | n.a. |
| | (0.42) | (-2.40) | (-1.40) | (-2.92) | (-3.12) | |
| qmj | -0.42 | -0.23 | 0.06 | 0.16 | 0.08 | – |
| | (-4.22) | (-2.35) | (0.48) | (1.31) | (0.72) | |
| qmj_growth | 0.15 | 0.06 | 0.25 | 0.16 | 0.20 | n.a. |
| | (2.25) | (0.85) | (2.21) | (1.41) | (1.72) | |
| qmj_prof | -0.80 | -0.20 | -0.25 | 0.11 | -0.05 | – |
| | (-7.31) | (-1.89) | (-2.01) | (1.08) | (-0.41) | |
| qmj_safety | -0.51 | -0.45 | -0.14 | -0.10 | -0.16 | – |
| | (-5.48) | (-4.17) | (-1.20) | (-0.80) | (-1.29) | |
| sale_bev | -0.21 | -0.23 | -0.09 | -0.11 | -0.09 | n.a. |
| | (-2.59) | (-2.97) | (-0.77) | (-1.07) | (-0.85) | |
| 10: SEASONALITY | | | | | | |
| corr_1260d | -0.92 | -0.38 | -0.22 | 0.13 | 0.03 | – |
| | (-8.37) | (-3.63) | (-1.64) | (0.98) | (0.20) | |
| coskew_21d | -0.18 | -0.17 | -0.13 | -0.11 | -0.16 | – |
| | (-3.33) | (-2.52) | (-1.48) | (-1.17) | (-1.43) | |
| dbnetis_at | -0.04 | -0.18 | -0.10 | -0.16 | -0.09 | n.a. |
| | (-0.78) | (-3.17) | (-1.28) | (-1.78) | (-1.11) | |
| kz_index | -0.04 | 0.20 | -0.33 | -0.20 | -0.25 | n.a. |
| | (-0.48) | (2.38) | (-2.73) | (-1.54) | (-1.86) | |
| lti_gr1a | -0.06 | -0.03 | -0.03 | 0.02 | -0.04 | n.a. |
| | (-1.13) | (-0.58) | (-0.36) | (0.27) | (-0.56) | |
| pi_nix | -0.11 | -0.06 | -0.16 | -0.13 | -0.22 | n.a. |
| | (-2.60) | (-1.04) | (-2.27) | (-1.77) | (-2.68) | |
| seas_11_15an | -0.02 | 0.00 | -0.16 | -0.14 | -0.10 | n.a. |
| | (-0.34) | (-0.02) | (-1.64) | (-1.44) | (-1.05) | |
| seas_11_15na | 0.07 | -0.07 | -0.04 | -0.14 | -0.09 | n.a. |
| | (1.10) | (-0.70) | (-0.34) | (-1.16) | (-0.76) | |
| seas_16_20an | 0.02 | 0.08 | 0.09 | 0.13 | 0.05 | n.a. |
| | (0.27) | (1.04) | (0.78) | (0.98) | (0.45) | |
| seas_2_5an | -0.16 | -0.20 | -0.20 | -0.24 | -0.16 | n.a. |
| | (-2.68) | (-2.57) | (-2.34) | (-2.39) | (-1.63) | |
| seas_6_10an | -0.07 | -0.02 | 0.06 | 0.09 | 0.05 | n.a. |
| | (-1.30) | (-0.32) | (0.59) | (0.80) | (0.37) | |
| sti_gr1a | -0.09 | -0.17 | 0.15 | 0.14 | 0.21 | n.a. |

*(continued)*

| Char. | (1) Mean | (2) $f^{\text{PHARMA}}$ | (3) TW*+ZHCT* | (4) TW*+ZHCT* $+f^{\text{PHARMA}}$ | (5) TW+ZHCT full | PHARMA impact |
|---|---|---|---|---|---|---|
| | (-1.15) | (-2.07) | (1.55) | (1.35) | (1.95) | |
| 11: SHORT-TERM REVERSAL | | | | | | |
| iskew_capm_21d | 0.05 | -0.03 | -0.01 | -0.05 | -0.03 | n.a. |
| | (0.77) | (-0.43) | (-0.07) | (-0.57) | (-0.31) | |
| iskew_ff3_21d | 0.05 | -0.06 | -0.04 | -0.12 | -0.10 | n.a. |
| | (0.90) | (-0.88) | (-0.42) | (-1.08) | (-0.92) | |
| iskew_hxz4_21d | 0.06 | -0.03 | -0.03 | -0.08 | -0.07 | n.a. |
| | (1.09) | (-0.47) | (-0.41) | (-0.90) | (-0.78) | |
| ret_1_0 | 0.03 | -0.14 | 0.15 | -0.04 | 0.11 | n.a. |
| | (0.25) | (-0.95) | (0.84) | (-0.20) | (0.58) | |
| rmax5_rvol_21d | -0.02 | -0.06 | -0.18 | -0.19 | -0.17 | n.a. |
| | (-0.21) | (-0.58) | (-1.51) | (-1.53) | (-1.14) | |
| rskew_21d | 0.07 | -0.05 | -0.09 | -0.16 | -0.17 | n.a. |
| | (1.03) | (-0.80) | (-1.02) | (-1.53) | (-1.73) | |
| 12: SIZE | | | | | | |
| dolvol_126d | -0.44 | -0.37 | -0.02 | 0.06 | 0.11 | – |
| | (-3.63) | (-2.78) | (-0.28) | (0.79) | (1.62) | |
| market_equity | -0.70 | -0.59 | 0.03 | 0.08 | 0.13 | – |
| | (-5.27) | (-3.73) | (0.37) | (0.83) | (1.79) | |
| rd_me | 0.58 | 0.05 | 0.27 | -0.05 | 0.15 | – |
| | (6.62) | (0.50) | (1.89) | (-0.35) | (1.06) | |
| 13: VALUE | | | | | | |
| at_me | -0.39 | 0.26 | -0.60 | -0.21 | -0.33 | n.a. |
| | (-2.54) | (2.07) | (-3.97) | (-1.44) | (-1.95) | |
| be_me | -0.23 | 0.26 | -0.52 | -0.21 | -0.32 | n.a. |
| | (-1.79) | (1.86) | (-3.87) | (-1.54) | (-2.16) | |
| bev_mev | -0.25 | 0.32 | -0.46 | -0.12 | -0.22 | n.a. |
| | (-1.69) | (2.08) | (-3.12) | (-0.82) | (-1.36) | |
| debt_me | -0.30 | 0.17 | -0.48 | -0.20 | -0.29 | n.a. |
| | (-2.68) | (1.61) | (-3.36) | (-1.44) | (-1.96) | |
| div12m_me | -0.41 | -0.18 | -0.34 | -0.21 | -0.20 | ✓ |
| | (-5.76) | (-2.59) | (-3.34) | (-2.04) | (-2.18) | |
| ebitda_mev | -0.93 | -0.15 | -0.56 | -0.12 | -0.35 | ✓✓ |
| | (-8.45) | (-1.76) | (-5.52) | (-1.31) | (-3.20) | |
| eq_dur | 0.48 | -0.05 | 0.39 | 0.11 | 0.23 | ✓ |
| | (4.01) | (-0.56) | (3.44) | (1.05) | (2.08) | |
| eqnetis_at | 0.66 | 0.18 | 0.28 | 0.07 | 0.11 | – |
| | (6.24) | (1.79) | (2.84) | (0.64) | (1.05) | |
| eqnpo_12m | -0.46 | -0.14 | -0.31 | -0.15 | -0.19 | – |
| | (-4.61) | (-1.67) | (-3.00) | (-1.45) | (-1.87) | |
| eqnpo_me | -0.70 | -0.25 | -0.35 | -0.11 | -0.16 | ✓ |
| | (-7.26) | (-2.76) | (-3.42) | (-1.16) | (-1.71) | |
| eqpo_me | -0.36 | -0.03 | -0.25 | -0.07 | -0.10 | – |
| | (-4.56) | (-0.43) | (-2.89) | (-0.78) | (-1.20) | |
| fcf_me | -0.37 | 0.03 | -0.12 | 0.12 | 0.04 | – |
| | (-4.38) | (0.34) | (-1.30) | (1.30) | (0.51) | |
| ival_me | 0.16 | 0.28 | -0.14 | -0.07 | -0.08 | n.a. |
| | (1.66) | (1.96) | (-1.31) | (-0.64) | (-0.72) | |

*(continued)*

| | (1) | (2) | (3) | (4) | (5) | |
|---|---|---|---|---|---|---|
| Char. | Mean | $f^{\text{PHARMA}}$ | TW*+ZHCT* | TW*+ZHCT* +$f^{\text{PHARMA}}$ | TW+ZHCT full | PHARMA impact |
| ni_me | -0.55 | -0.08 | -0.21 | 0.04 | -0.14 | – |
| | (-6.33) | (-0.91) | (-2.18) | (0.41) | (-1.33) | |
| sale_me | -0.82 | 0.02 | -0.96 | -0.45 | -0.64 | ✓✓ |
| | (-5.97) | (0.22) | (-7.65) | (-3.61) | (-4.26) | |

# D News data and jump surprises

## D.1 Filtering RavenPack news data

I apply several data filters to obtain a clearer picture of news events associated with stock return jump surprises. I rely on the RavenPack 4.0 Equities (Full Edition), which facilitates the detection of novel news due to the availability of an event novelty score. I match firms in the RavenPack database to my option and stock data using CUSIP codes, which I obtain from the matching table provided by WRDS. Note that these filters do *not* result in a unique event or news observation per jump day. Instead, I obtain novel news of distinct events (which could technically occur on the same day) for each jump day observation in my sample.

I start by only considering news events on the day of (positive or negative) stock jumps identified according to Section 5.2 in the main paper. To ensure that news events affect stock prices on a given day, I only retain news with a timestamp after 16:00:00 ET on the day *before* the jump date and before 16:00:00 ET on the *same* day. Subsequently, I apply the following filters:

- I only keep events with a relevance score and global event novelty score (G_ENS) of 100. A relevance score of 100 ensures that the firm is prominently featured in the news story. The G_ENS of 100 filters the most novel news stories within a 24-hour time window across all news providers covered by RavenPack. I thereby keep only novel news headlines and considerably reduce the redundancy of including the same news story (with multiple releases) multiple times.

- I delete news events in the following groups, the second highest level of the RavenPack Event Taxonomy: "stock-prices", "order-imbalances", "equity-actions", "analyst-ratings", and "price-targets". Stock price events, order imbalances, and equity events such as trading halts are directly related to stock returns and extreme price movements. Analyst ratings and price targets are typically a reaction to stark price movements caused by other firm-specific events.

- I further exclude news of the type "earnings-per-share" (third highest level of the RavenPack Event Taxonomy). News stories of this type are typically duplicates of the general 'earnings' related news type.

- Finally, I only consider news groups with at least 100 occurrences for pharmaceutical firms.

### D.2 Examples for jump surprise headlines

The following tables list examples of news headlines by RavenPack news groups for pharmaceutical firms, see Table 9. Headlines are extracted from RavenPack 1.0 (Full Edition). The tables include the news headlines for the two events on the jump days with the highest absolute jump surprise.

**News headlines on positive jump surprise days**

| Company name | Date | Headline | Comment |
|---|---|---|---|
| PRODUCTS-SERVICES | | | |
| Vanda Pharmaceuticals Inc. | 2009-05-06 | UPDATE 1-Vanda gets FDA nod for schizophrenia drug | – |
| Seres Therapeutics Inc. | 2020-08-10 | Seres Therapeutics reports 'positive' results from Phase 3 ECOSPOR III study | – |
| ACQUISITIONS-MERGERS | | | |
| Human Genome Sciences Inc. | 2012-04-19 | Human Genome Rejects $2.6B Takeover Bid | – |
| Foundation Medicine Inc. | 2015-01-12 | Update: Roche to Buy 56.3% of Foundation Medicine in $1.03 Billion Deal - FMI Shares Soaring 100% | Stock price jumped regardless of rejected bid as investors predicted that a sale would go through eventually. |
| INVESTOR-RELATIONS | | | |
| Sarepta Therapeutics Inc. | 2012-10-02 | Sarepta Therapeutics Announces Conference Call and Webcast on Wednesday, October 3, 2012, to Discuss 48-Week Results From the Phase IIb DMD Study | – |
| Zogenix Inc. | 2017-09-29 | Zogenix to host conference call | – |
| PARTNERSHIPS | | | |
| Aralez Pharmaceuticals Inc. | 2005-04-21 | Pozen, GlaxoSmithKline Collaborating On Pdt | Collaboration of subsidiary. |
| Five Prime Therapeutics Inc. | 2015-10-15 | Five Prime Therapeutics (FPRX) Enters Collaboration with Bristol-Myers Squibb (BMY) Worth Up to $1.74B | – |
| TECHNICAL-ANALYSIS | | | |
| InterMune Inc. | 2014-02-25 | CHART InterMune Inc ST: the RSI is overbought | – |

**News headlines on positive jump surprise days** *(continued)*

| Company name | Date | Headline | Comment |
|---|---|---|---|
| Neurocrine Biosciences Inc. | 2014-01-07 | CHART Neurocrine Biosciences Inc ST: the RSI is overbought | – |
| LABOR-ISSUES | | | |
| Karyopharm Therapeutics Inc. | 2020-03-02 | KARYOPHARM THERAPEUTICS : Appoints Richard Paulson to its Board of Directors | – |
| Karyopharm Therapeutics Inc. | 2019-07-03 | Karyopharm Therapeutics: Anand Varadan Resigns as Executive VP, Chief Commercial Officer | Resignation after the buildout of the company's commercial organization, coinciding with the announcement of an FDA approval. |
| MARKETING | | | |
| ChemoCentryx Inc. | 2019-11-26 | ChemoCentryx to Present at the 31st Annual Piper Jaffray Healthcare Conference | – |
| Sarepta Therapeutics Inc. | 2016-09-19 | UPDATE: Sarepta Release Shows US Commercial Launch Planned to Commence Immediately; Mgmt to Host Call at 4 p.m. EDT to Discuss | Conference call related to positive clinical study result |
| INSIDER-TRADING | | | |
| Regulus Therapeutics Inc. | 2014-10-21 | CEO XANTHOPOULOS Sells 700 Of REGULUS THERAPEUTICS INC RGLS | – |
| Reata Pharmaceuticals Inc. | 2019-10-15 | Officer Castellanos Sells 3,000 Of Reata Pharmaceuticals Inc RETA | – |
| EARNINGS | | | |
| Fulcrum Therapeutics Inc. | 2021-08-10 | Fulcrum Therapeutics 2Q Loss $19.6M FULC | – |
| Allakos Inc. | 2019-08-05 | Allakos 2Q Loss $19.1M ALLK | – |
| REVENUES | | | |

**News headlines on positive jump surprise days** *(continued)*

| Company name | Date | Headline | Comment |
|---|---|---|---|
| Lexicon Pharmaceuticals Inc. | 2021-01-14 | Zacks: Brokerages Expect Lexicon Pharmaceuticals, Inc. (NASDAQ:LXRX) Will Announce Quarterly Sales of $170,000.00 | – |
| Concert Pharmaceuticals Inc. | 2017-03-06 | Concert Pharmaceuticals 4Q Rev $21,000 CNCE | – |

**News headlines on negative jump surprise days**

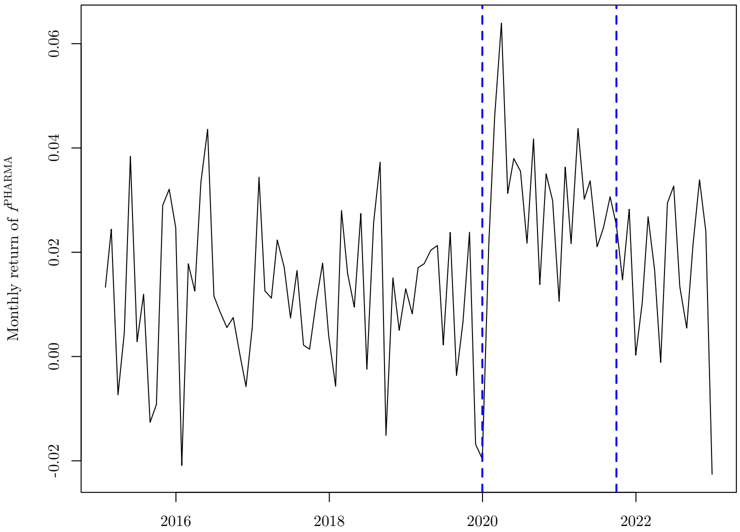
| Company name | Date | Headline | Explanation |
|---|---|---|---|
| PRODUCTS-SERVICES | | | |
| Chimerix Inc. | 2015-12-28 | Chimerix Fails To Meet Primary Endpoint In Phase 3 Trial Of Brincidofovir In CMV Prevention – Trading Halted til 8 a.m. ET | – |
| Cortexyme Inc. | 2021-10-26 | Cortexyme's Alzheimer's Drug Trial Fails to Meet Main Goals, Shares Plunge 71% After-Hours | – |
| INVESTOR-RELATIONS | | | |
| AFFYMAX INC. | 2010-06-20 | Affymax(R) to Hold Conference Call and Webcast on Monday, June 21, 2010 at 8:00 a.m. Eastern Time | Conference call in related to announcement of patients suffering heart-related side effects in Phase III trials |
| Solid Biosciences Inc. | 2019-02-07 | Solid Biosciences to host conference call | – Conference call related to disappointing preliminary results from the Phase I/II study |
| LABOR-ISSUES | | | |
| NextCure Inc. | 2020-07-13 | NextCure: Chief Medical Officer Kevin Heller Resigned Effective Aug 4 NXTC | – |
| Five Prime Therapeutics Inc. | 2017-11-06 | Five Prime Therapeutics: Rusty Williams Will Be Named Executive Chmn FPRX | – |
| REVENUES | | | |
| Dendreon Corp. | 2011-08-03 | Dendreon 2Q Rev $49.6M DNDN | – |
| ChemoCentryx Inc. | 2021-05-07 | ChemoCentryx, Inc. (NASDAQ:CCXI) Expected to Post Quarterly Sales of $4.99 Million | – |
| EARNINGS | | | |
| Dermira Inc. | 2018-03-05 | FY2022 EPS Estimates for Dermira Inc Lowered by Leerink Swann (NASDAQ:DERM) | – |

**News headlines on negative jump surprise days** *(continued)*

| **Company name** | **Date** | **Headline** | **Explanation** |
|---|---|---|---|
| AnaptysBio Inc. | 2019-11-08 | AnaptysBio Announces Third Quarter 2019 Financial Results and Provides Pipeline Updates | – |
| TECHNICAL-ANALYSIS | | | |
| Progenics Pharmaceuticals Inc. | 2012-07-30 | CHART Progenics Pharmaceuticals Inc ST: above its upper Bollinger band | – |
| Halozyme Therapeutics Inc. | 2012-08-02 | CHART Halozyme Therapeutics Inc ST: the RSI is oversold | – |
| INSIDER-TRADING | | | |
| Adverum Biotechnologies Inc. | 2015-06-15 | CFO BAIN Sells 3,500 Of AVALANCHE BIOTECHNOLOGIES INC AAVL | – |
| Solid Biosciences Inc. | 2021-03-15 | COO Schneider Surrenders 23,398 Of Solid Biosciences Inc SLDB | – |
| ACQUISITIONS-MERGERS | | | |
| Akorn Inc. | 2018-10-01 | Delaware Court Rules For Fresenius In Disputed Akorn Merger; Judge Says Fresenius Validly Terminate Merger Agreement With Akorn, Says Akorn's Merger Representations To Fresenius Were Not True | – |
| OncoGenex Pharmaceuticals Inc. | 2009-12-21 | Teva Pharmaceutical To Acquire Shares In OncoGenex | – |

## E Additional time-series analyses

(a) Baseline $f^{\text{PHARMA}}$




(b) Long leg of $f^{\text{PHARMA}}$

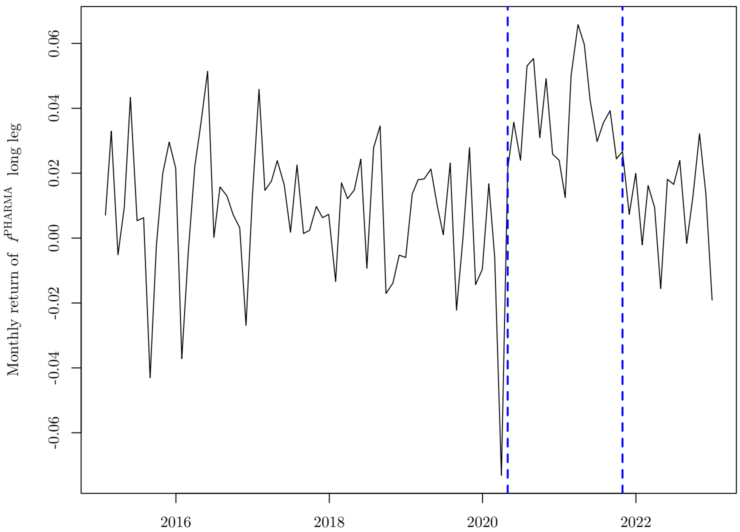
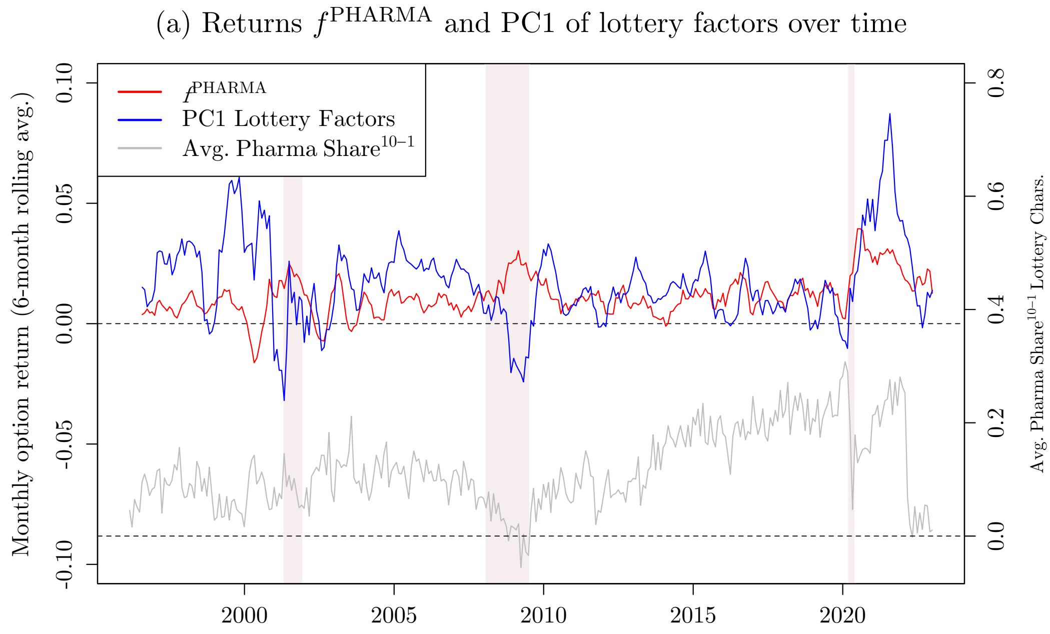



**Fig. E1. Breakpoints in $f^{\text{PHARMA}}$ mean returns**

This figure plots the monthly return of $f^{\text{PHARMA}}$ from January 2015 until December 2022 and indicates structural breakpoints identified by the Bai and Perron (1998, 2003) test (vertical blue lines). Panel (a) includes the baseline $f^{\text{PHARMA}}$ factor that is long in options on pharmaceuticals and short in options on all other stocks. Panel (b) depicts only the *long leg* of $f^{\text{PHARMA}}$.



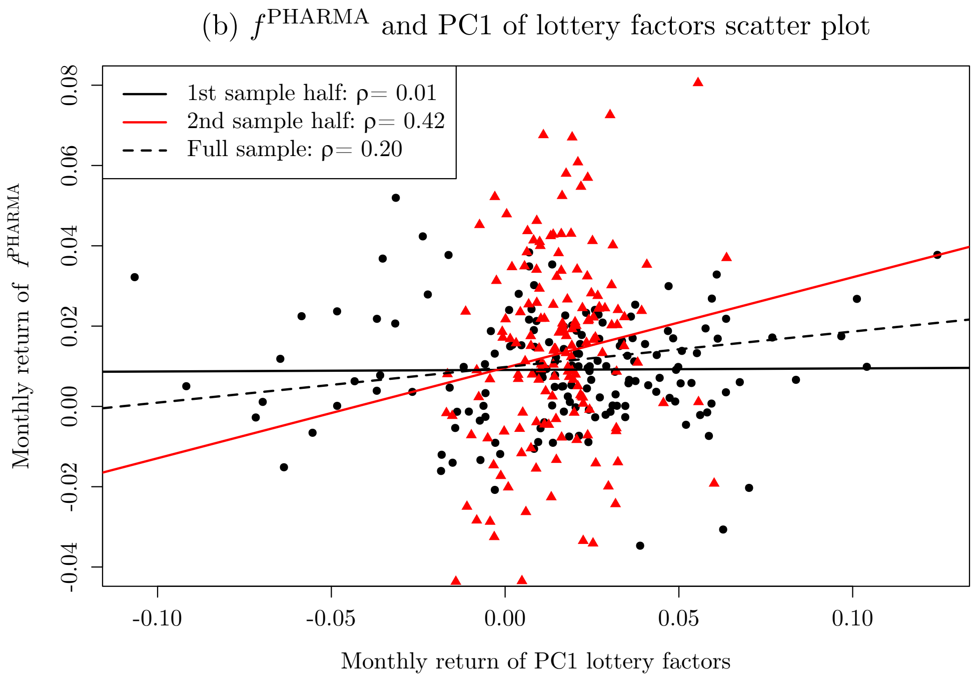




**Fig. E2. Pharmaceutical option factor and lottery stocks**

Panel (a) of this figure plots six-month rolling average returns of the $f^{\text{PHARMA}}$ (red) and the first principal component (PC1) of lottery option factors used by Jones et al. (2024) (blue). The lottery characteristics include expected skewness, jackpot probability, and maximum return detailed in Internet Appendix B.4, as well as the -PRICE and IVOL characteristics from the baseline ZHCT anomalies. The gray line indicates the average difference between the share of pharmaceuticals in decile 10 and decile 1 for the five lottery characteristics. Panel (b) plots individual monthly return observations of $f^{\text{PHARMA}}$ and VRP. Lines are based on fitting a linear regression of $f^{\text{PHARMA}}$ on VRP for the 1st and 2nd sample halves and the full sample. The sample period is 02-1996 to 12-2022.

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