# Lockdowns and Leverage: Option Pricing during the Covid Pandemic

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**Abstract**

We show that option risk premia shift abruptly at the start of the Covid lockdown, a period associated not only with the onset of novel financial market risks, but also with an unprecedented surge in retail trading. While our evidence is consistent with a general increase in the magnitude of option risk premia during the lockdown, the shift is far larger for options on stocks favored by retail traders. In contrast, effects related to Covid exposure or systematic risk are modest. Retail option demand is much higher for stocks more likely to attract traders with preferences for lottery-like payoffs. A factor that captures lottery preferences in options explains most of the shift in option risk premia.

*Keywords*: Options; Retail trading; Covid pandemic

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# 1 Introduction

The Covid-19 pandemic and associated global lockdown had unprecedented effects on market risk, economic growth, and investor behavior. The CBOE's volatility index spiked to four times its average level, and stay-at-home orders reduced consumption by the largest amount on record. With no commensurate drop in personal income due to the initiation of government stimulus payments, the household savings rate approximately doubled in the first year of the lockdown (Aladangady, Cho, Feiveson, and Pinto 2022), and many invested those savings for the first time in the financial markets.

These new investors were younger, and a large fraction expressed the explicit goal of trading for short-term gains (Schwab 2021). Many of these investors found enticement in the options market, with Google search volume for the term "option trading" tripling by March 2020 relative to steady 2019 levels. The share of retail trading on the CBOE jumped suddenly between February and March 2020 from 35% to 47% of total volume (Poser 2023), precisely coinciding with the first stay-at-home orders in the U.S. At the four leading retail brokers, payment for order flow, which is mostly from options trading (Bryzgalova, Pavlova, and Sikorskaya 2023; Ernst and Spatt 2024), more than doubled between 2019 and 2020. At Robinhood, it grew ten-fold (Rowady 2021).

Given the strong demand effects on option pricing documented by Garleanu, Pedersen, and Poteshman (2008), it is natural to expect some kind of pricing impact from these sudden shifts. Assessing and understanding these shifts is the goal of this paper.

Different from prior work that focuses on retail trading effects at the individual option level (Bryzgalova, Pavlova, and Sikorskaya 2023, Eaton, Green, Roseman, and Wu 2024), our focus is on systematic pricing effects. As in the equity literature, a convenient way to describe risk premia is via factor portfolios, long-short portfolios formed on the basis of firm-level characteristics. In the options literature, well known examples of such characteristics include the difference between historical and implied volatility (Goyal and Saretto 2009) and idiosyncratic stock volatility (Cao and Han 2013). We examine these characteristics and eight others.

Our first set of results documents large and highly significant shifts in option factor risk premia at the start of the Covid lockdown. Eight out of ten factors exhibit a single structural break, as identified by the Bai and Perron (1998) test, between March and April of 2020. One factor shows a break later the same year, and one factor shows no significant breakpoints. In all cases, the 2020 breakpoint has the effect of magnifying, rather than shrinking or reversing, whatever risk premia existed prior to the break. Remarkably, eight out of the ten factors do not show a single negative return in the 21-month period between April 2020 and December 2021.

We find that these breaks in factor risk premia are much larger when factors are constructed from stocks favored by retail traders. High retail activity is associated with a March 2020 decline in average returns on both the long and short sides of the long-short factor portfolios, but the effects tend to be much larger on the short sides. Options on stocks with high retail activity may have, during the Covid period, twice the (negative) average return of options on stocks with low retail activity.

These relations are associative and not necessarily causal, and it is possible that retail traders may be drawn to firms whose options underperform for other reasons. An obvious possibility is that investors were drawn to options on firms that were more sensitive to pandemic-related risks, and that these firms had more negative risk premia as a result of their properties as Covid hedges.

We examine Covid sensitivity in two ways. The first is to sort firms by the Covid exposure measure of Hassan, Hollander, Van Lent, Schwedeler, and Tahoun (2023). When doing so, we find only small differences between factors constructed from firms with high or low exposure.

Second, we examine industry-level and industry-adjusted retail trading, with the motivation that the impact of the Covid pandemic had a a large industry component (e.g., hospitality vs. software). While industries with high retail involvement show slightly greater shifts at the start of the pandemic, industry-adjusted retail trading is far more related, implying much stronger within-industry effects that also appear inconsistent with our findings capturing premia for Covid risk.

With support for retail trading as a potential source of the structural shifts in factor returns, we next focus how the retail trading measures vary with option return predictors. We use proxies for stock and option retail trading from Boehmer, Jones, Zhang, and Zhang (2021) and Bryzgalova, Pavlova, and Sikorskaya (2023), respectively, in each case dividing our measure of retail volume by total volume to obtain a stock or option "retail ratio" for each firm.

We examine average stock and option retail ratios for the ten long-short anomaly portfolios. We find that option retail ratios are, on average, higher for options on the short side for nine out of ten portfolios, with eight differences statistically significant. Options held short also have higher stock retail ratios for eight out of the ten portfolios, usually by large margins. Thus, overall, retail trading – both in stocks and options – tends to concentrate in firms whose options exhibit characteristics known to result in poor performance. This may explain the poor performance of retail traders found by Bryzgalova, Pavlova, and Sikorskaya (2023) and de Silva, Smith, and So (2023).

Retail ratios themselves also exhibit a shift between the pre- and post-March 2020 periods. Similar to the CBOE's finding of an increase in retail option trading at this time (Poser 2023), we confirm that stock retail trading also increased. More importantly, this increase was larger for options held short in nine out of the ten anomaly portfolios. Thus, precisely at the time that retail traders became interested in these stocks, their option returns changed starkly for the worst.

We construct a retail factor by sorting firms by their stock retail ratios, with options on firms with low retail trading held long. Not surprisingly, this factor also exhibits a March 2020 breakpoint. It is also positive in every month between April 2020 and December 2021, again indicating the poor Covid-era performance of options on firms popular with retail traders. Moreover, this factor explains, on average, about half of the structural shifts in the individual anomaly portfolios.

Our final set of results examines potential drivers of retail interest. Several papers, starting with Boyer and Vorkink (2014) propose lottery preferences as an explanation of retail trading in stock options. Filippou, Garcia-Ares, and Zapatero (2022) argue that skewness-seeking investors generally prefer trading options to stocks. Bryzgalova, Pavlova, and Sikorskaya (2023) conclude that gambling, rather than hedging, is the most likely motive for retail trading in options. These findings contrast with Bogousslavsky and Muravyev (2024), who examine a sample of retail traders' holdings and find no evidence of lottery-seeking behavior.

We also consider extrapolative beliefs and attention as other sources of retail activity. The extensive literature on extrapolation has recently been brought to the options setting by Atmaz (2022), who constructs a model in which the extrapolation of positive returns leads to downward-biased expectations of future volatility. A relation between attention and option prices was demonstrated by Choy and Wei (2023), who show that retail trading is higher for stocks with extreme past returns.

We find that retail trading, both in stocks and options, is highly related to all lottery proxies. While trend and attention show some significant relations to retail trading, neither adds much relative to the explanatory power of lottery preferences. Moreover, lottery proxies are almost uniformly higher for options held on the short sides of the ten anomaly portfolios.

We construct long-short option portfolios based on five different lottery characteristics. All five portfolios exhibit a break in March 2020, as does a summary lottery factor calculated as the first principal component of the five portfolios. After controlling for this lottery factor, we find that the structural breaks in the ten anomaly portfolios are substantially reduced, becoming insignificant in most cases.

Overall, our results are consistent with a rise in lottery-motivated retail trading at the start of the pandemic. This shift was large enough to substantially affect option risk premia, in many cases doubling average factor returns over their pre-pandemic levels. Our results add to existing evidence, such as Eaton, Green, Roseman, and Wu (2024) and Lipson, Tomio, and Zhang (2023), that shows that retail trading can affect option prices. We expand on these findings by showing evidence that retail trading may have large, broad, and long-lasting impacts on the options market, which results in considerable changes to the factors commonly examined in empirical options research. Our research also helps to understand the sources of option trader underperformance documented by Bryzgalova, Pavlova, and Sikorskaya (2023). Retail trading is concentrated in firms exhibiting characteristics demonstrated to result in low option returns. This tendency existed long before the Covid pandemic, but it intensified dramatically at the start of the lockdown.

In the next section, we discuss the construction of option factor portfolios. Section 3 shows our primary evidence of structural breaks in option factors. Section 4 examines the relation between factor characteristics and retail trading, while Section 5 looks at the determinants of retail trading. Section 6 concludes.

# 2 Option factors

## 2.1 Data sources

Our primary sample comprises options on individual equities over the period from January 2015 to December 2022, sourced from the OptionMetrics database. The database contains several distinct files. The option price file includes closing bid and ask prices, option deltas, trading volume, expiration dates, and open interest. Closing stock prices are retrieved from the security price file. The volatility surface file is utilized to construct risk-neutral moments and other firm-level characteristics. Additionally, historical volatility data based on a trailing 365-day window is obtained from the OptionMetrics historical volatility file. Zero-coupon interest rates are derived from the zero-coupon yield curve. Some analysis additionally uses options on the S&P 500 (SPX) Index.

Stock prices and returns are obtained from the CRSP stock file, which is cross-verified with OptionMetrics data. Furthermore, we use the CRSP stock file to determine market capitalization for the construction of size portfolios. Some firm-level characteristics are also derived from COMPUSTAT data.

Finally, we obtain trade-level data for stocks and options, which we use to estimate retail trading volumes, from TAQ and Polygon.io, respectively.

## 2.2 Construction of delta-hedged call returns

At the end of the third Friday of each month, we form one delta-hedged (DH) call position for each stock (CRSP share code 10 or 11 and exchange code 1, 2, or 3). We choose among calls expiring on the third Friday of the next month, implying that our holding periods are either four or five weeks in length. We exclude options on firms with dividends during the holding period if those dividends have been announced as of the portfolio formation day.

We discard options with zero open interest or trading volume on the day of portfolio formation, and we require the option's moneyness (the ratio of stock to strike prices) to be between 0.9 and 1.1. We exclude options with missing deltas, those with bid-ask spreads that are above \$5 or smaller than the minimum tick size.[1] We also exclude calls whose midpoint is less than the value of immediate exercise ($\max\{S-K,0\}$). Out of these, we retain the call with delta closest to 0.5.

On each day $t$ up to the day before expiration, and for each stock, we form a zero investment portfolio by

- holding one call, with price $C_t$,
- shorting $\Delta_t$ shares of stock, with value $\Delta_t S_t$, and
- investing $\Delta_t S_t - C_t$ in a risk-free account.

For call prices, we use the bid-ask midpoint, while stock prices are closing values. $\Delta_t$ is the Black-Scholes delta computed by OptionMetrics.

These DH call portfolios are held until expiration. On occasion, the delta is missing from OptionMetrics. In this case, we calculate the delta using the Black-Scholes formula using the option's most recent non-missing implied volatility.

The DH portfolio return is calculated as:

$$\frac{\max(S_T-K,0)-C_0-\sum_{\tau=0}^{T-1}\left(\Delta_t(S_{\tau+1}-S_\tau)-r_{f,\tau}(C_\tau-\Delta_\tau S_\tau)\right)}{S_0} \tag{1}$$

where $T$ denotes the total number of days during the holding period and $r_{f,\tau}$ is the one-day Libor risk-free rate. Following Bakshi and Kapadia (2001), Büchner and Kelly (2022), and Tian and Wu (2021), we use the initial stock price rather than the option price in the denominator. As noted by Fournier, Jacobs, and Orłowski (2024), this normalization avoids a microstructure bias discussed by Duarte, Jones, and Wang (2022).

[1] The tick size is \$0.1 if the bid is greater than \$3 or \$0.05 otherwise.

The primary analysis focuses on delta-hedged calls. However, delta-hedged put returns are studied for robustness. The construction of delta-hedged puts mirrors that of calls.

## 2.3 Option return predictors

We analyze a set of variables that have been shown to be predictive of future option returns. For each characteristic, we sort firms into deciles, and equally-weighted average delta-hedged call returns are calculated for each decile. A long-short portfolio is formed from the two extreme decile portfolios, with the long side selected to have the higher average return over the period from January 2015 to March 2020.

The characteristics included are listed below, along with a description of whether the high decile is held long or short:

- implied volatility (Bali, Beckmeyer, Moerke, and Weigert 2023; Büchner and Kelly 2022) – low values long
- risk-neutral variance (Horenstein, Vasquez, and Xiao 2023) – low values long
- risk-neutral skewness (Bali and Murray 2013) – low values long
- risk-neutral kurtosis (Bali, Beckmeyer, Moerke, and Weigert 2023) – high values long
- implied volatility term spread (Vasquez 2017)– low values long
- market capitalization (Zhan, Han, Cao, and Tong 2021) – high values long
- option bid-ask-spread (Christoffersen, Goyenko, Jacobs, and Karoui 2018)– low values long
- volatility risk premium (Goyal and Saretto 2009)– high values long
- past 12-month option return (Heston, Jones, Khorram, Li, and Mo 2023) – high values long

- idiosyncratic volatility (Cao and Han 2013) – low values long

The relation between these characteristics and average option returns matches that of the original papers, in sign if not in magnitude. The exception is the option bid-ask-spread, which Christoffersen, Goyenko, Jacobs, and Karoui (2018) find to be positively related to future option returns. Our finding of a negative relation mirrors Vasquez and Xiao (2023).

We also compute the equal weighted portfolio of delta-hedged calls using all firms as well as a delta-hedged portfolio return for the S&P 500 Index. Construction details are in the appendix.

## 2.4 Measuring retail trading

We use procedures developed in two recent papers to extimate retail trading in stocks and options.

For stocks, our measure of retail trading follows Boehmer, Jones, Zhang, and Zhang (2021). This algorithm makes use of the tendency of retail trades to be filled off-exchange, where they receive price improvement. TAQ trades that occur inside the prevailing bid-ask spread and that appear on the Trade Reporting Facility, rather than an exchange, are assumed to represent retail trades. These trades may be signed according to whether the price is above or below the mid-quote, though we do not make use of this feature.[2]

For estimates of option retail volume, we use data from Polygon.io and apply the approach of Bryzgalova, Pavlova, and Sikorskaya (2023). This method identifies trades as retail when they use the single leg auction mechanism, which appears as a trade condition in the SIP starting in November of 2019.

In each case, we aggregate to monthly by summing retail volume over the period starting from the fourth Monday of the previous month to the third Thursday the current month,

[2]Unreported robustness results use the alternative method of Barber, Huang, Jorion, Odean, and Schwarz (2023) instead. This has little effect on our results.

one day before we form delta-hedged option positions. We then divide by the total trading volume over the same period, which we term the "retail ratio." In the case of options, retail and total volumes include all contracts on a given stock, not only the contract whose delta-hedged return we analyze.

Because neither method captures all retail trades, only a fraction that are most easily identified, this ratio should be interpreted somewhat loosely. Our requirement is only that it is correlated with the true fraction of retail trades.

# 3 Evidence for structural change

## 3.1 Breakpoint analysis

A primary objective of this paper is to investigate the occurrence and timing of structural changes in the historical returns of option portfolios. Based on the visual evidence presented in Section 1, a pattern of structural breaks appears to occur around the onset of the Covid pandemic. In this section, we formally test the existence of these breakpoints and evaluate the magnitude of the associated structure changes.

We begin by testing the occurrence of breakpoints with the monthly portfolio return spanning from the beginning of 2015 to the end of 2022. The structural break test of Bai and Perron (1998, 2003) is applied, which identifies both the number and timing of breakpoints.

Results are presented in Table 1. Out of the ten long-short portfolios we analyze, eight exhibit a breakpoint immediately after March 2020. More specifically, the return whose holding period ends on March 20, 2020 is the last one prior to the breakpoint. This breakpoint therefore coincides precisely with the beginning of the Covid pandemic in the United States, which was declared a national emergency in the United States on March 13, 2020. Moreover, the first stay-at-home order in the U.S., issued by the State of California, was about a week later, on March 19.[3]

Results are different for the other two long-short portfolios. The portfolio based on the implied volatility term spread shows no significant evidence of a breakpoint, and the portfolio based on option momentum shows a breakpoint after October 2020. Between the two long-only portfolios, the EW average of delta-hedged calls shows a breakpoint in April 2020, while the SPX portfolio shows no significant breaks.

Among the 12 portfolios, five exhibit a secondary breakpoint in either October of November of 2021. From Figure 1, it is evident that the first breakpoint is associated with a substantial rise in anomaly returns. Conversely, portfolios displaying a second breakpoint show a decline in anomaly returns. We focus on examining the impact of the initial structural break on anomaly returns. To mitigate the noise introduced by the second structural break, our subsequent analysis is restricted to data up to December 2021.

With the structural change reasonably consistent at the outset of Covid across the portfolios we analyze, we then turn to measuring the magnitude of these changes. To accomplish this, we simply examine the difference in portfolio returns before and after the breakpoint in March 2020. Specifically, the following regression is applied for this analysis:

$$R_{p,t} = \alpha_p + \beta_p I_t + \epsilon_{p,t} \, , \tag{2}$$

Here $R_{p,t}$ is the return for portfolio $p$ at month $t$, and $I_t$ is a month dummy with value 1 after March 2020. The value of the intercept, $\alpha_p$, measures the economic significance of the average option portfolio return prior to the pandemic. The slope coefficient, $\beta_p$, reflects the economic magnitude of the structural change.

The results of these regressions are presented in columns 1 and 2 of Table 2. For ten long-short portfolios, $\alpha_p$ is significant and positive, confirming the existing literature on these

[3]CDC Museum Covid-19 Timeline, https://www.cdc.gov/museum/timeline/Covid19.html

anomalies.[4] Averaging across the ten portfolios (the "Average H-L" row), we find an average $\alpha_p$ of approximately 0.007, or 8% annualized, indicating economic significance. **Sharpe ratios?**

Reflecting the findings in Table 1, all but one of the long-short portfolios exhibit a significant $\beta_p$, consistent with structural change at this time. What is novel in this table is that all of the $\beta_p$ estimates are positive, indicating that the structural break led to a magnification of the pre-break average return spreads. Moreover, the $\beta_p$ estimates are large, on average almost 50% greater than the corresponding $\alpha_p$ estimates. This implies that post-break returns are on average more than double the pre-break values. **Sharpe ratios?**

We also run regression 2 separately for long and short legs. These results are presented in columns 3-6 of Table 2. We observe that the $\alpha_p$ coefficient is generally insignificant for long legs but significantly negative for short legs. In other words, pre-break profitability of the long-short strategies arises almost entirely from the short legs. This is consistent with many findings in the option literature.

In contrast, the $\beta_p$ coefficient is negative and significant across every long and every short portfolio. This includes the cross-sectional EW average portfolio and the return on S&P 500 Index options, both of which are included in columns 3-4. Neither one shows a statistically significant $\alpha_p$, indicating little evidence of nonzero average returns before March 2020. Both, however, show negative and highly significant estimates of $\beta_p$.

Overall, the results in this table demonstrate that the 2020 structural break is large and pervasive, leading to more negative returns in every option category analyzed. The response to the break is not uniform, however. Options with low returns before the break tended to have even lower returns after the break. These differential responses result in changes to long-short returns.

[4] Recall that positivity of the $\alpha_p$ is by construction, though statistical significance is not.

Given the apparent structural breaks in the cross-sectional EW average portfolio and in the S&P 500 Index, it is natural to ask whether the breakpoints in long-short portfolios are a mechanical consequence. To investigate this, we run the following regression:

$$R_{p,t} = \alpha_p + \beta_p I_t + \gamma_p CS_t + \epsilon_{p,t}\,, \tag{3}$$

where $CS$ represents the cross-sectional average delta-hedged return. If the break in the cross-sectional average portfolio explains that of the long-short factor, the $\beta_p$ estimate in regression 3 should be insignificantly different from zero.

The regression results presented in columns 7 and 8 of Table 2 strongly refute this hypothesis. Although the $\beta_p$ coefficients become moderately smaller, they remain significant for nearly all anomalies. This implies that the structural breaks in option returns are not closely related to the option's sensitivity to aggregate option market risk. Similar results are obtained when we use the S&P 500 Index option return instead of the cross-sectional average portfolio, but we do not report these results for brevity.

## 3.2 Heterogeneity in break size: retail trading

To investigate the hypothesis that structural breaks are driven by retail investors, we examine whether structural breaks differ between stocks favored or not favored by retail investors. We base this analysis on the same long and short portfolios studied in Tables 1 and 2. Here, however, each long and short portfolio is split into halves according to each firm's most recent stock retail ratio. Firms with a stock retail ratio above the cross-sectional median retail ratio of their respective decile are classified as having high retail ratios, while those with ratios below the median are classified as having low retail ratios. We then construct long-short portfolio returns from both the high retail ratio firms and, separately, from the low retail ratio firms.

The average returns from January 2015 to March 2020, and the changes in returns after

March 2020 (representing the magnitude of the structural break) for these two long-short portfolios, are estimated from the intercepts and coefficients from the regression (2). These results are plotted in Panels A and B of Figure 2.

Panel A shows pre-break average returns, where each dot in the scatter plot represents one characteristic. The value on the x axis represents the pre-break average return for the long-short portfolio formed from firms with low stock retail ratios. The value on the y axis shows the corresponding average return for stocks with high retail ratios. The shading of each dot denotes the statistical significance of the difference between the long-short portfolios with high and low retail ratios.

Panel A shows that pre-break long-short returns are, for all characteristics, higher among firms with high retail ratios. The differences are statistically significant for five out of ten characteristics, at the 1% level for four of the five. Thus, the degree of retail interest may proxy for the level of mispricing underlying the various anomaly portfolios.

We plot the magnitude of the structural break in Panel B of Figure 2. Similar to Panel A, each dot represents one anomaly, with the x-axis/y-axis showing the value for the low/high retail ratio group. The dot shading again indicates statistical significance.

Of the ten anomalies, eight are above the 45-degree line, and all eight show a significant difference in the size of the structural break. This indicates a more pronounced effect of retail investors on anomaly returns after the breakpoint. Only two characteristics are below the 45-degree line. The implied volatility term spread shows an insignificant difference in the structural break size, consistent with the apparent absence of a structural break for this anomaly indicated in Tables 1 and 2.

Panels C to F show similar results for the long and short sides of the portfolios separately. For the options held long, shown in Panels C and D, there is little evidence of any relation between retail activity and average returns, either before or after March 2020. Thus, the retail patterns in long-short returns are entirely driven by the short side, as confirmed in Panels E and F. Options with more retail interest are likely to be more overpriced prior to the beginning of the Covid period. At that point, their negative average returns **perhaps double in magnitude.**

Ideally, we would perform the same analysis using the option retail measure of Bryzgalova, Pavlova, and Sikorskaya (2023). As noted above, however, this measure is only available starting in November of 2019. It is therefore impossible to estimate, with any precision, the pre-March 2020 average return or, as a result, the change in average returns around March 2020. We will therefore focus only on the level of average returns after March 2020. While these results will not speak directly to the drivers of the apparent structural break at this time, they should nevertheless show whether the negative relation between average option returns and retail interest also holds when retail interest is measured from options.

Panel A of Figure 3 shows average long-short return over the sample period starting in 2020 for firms with either high or low option retail ratios. Similar to the previous figure, Panels B and C show long and short legs separately, and points above the 45 degree line indicate that high retail ratios are associated with higher returns. For most long legs, retail trading is unrelated to average returns. In three cases (option bid-ask spread, momentum, and IV term spread), higher retail trading is associated with significantly lower returns. For the short legs, this negative association is present for all but one characteristic.

These results are therefore consistent with those from stock retail trading: Options with higher retail interest generally perform worse, but this is particularly true among options that our characteristic-based portfolios would hold short.

## 3.3 Heterogeneity in break size: Covid exposure

The previous results demonstrate strongly that options on stocks favored by retail investors tend to have more variation in their expected returns, in particular with more options having very negative average returns. Furthermore, this relation appears to have strengthened substantially after a structural break around the start of the Covid lockdown. This does not, of course, imply that retail trading is causal in generating lower option returns. Retail traders may simply be drawn to firms that happen, for some reason, to have options with more negative risk premia, perhaps because those options are more effective at insuring against some risk.

While we are unable to refute this possibility generally, we can examine the obvious special case of Covid exposure being the underlying driver of the structural break. If retail investors favored buying options on stocks with a higher exposure to Covid-related risks, then a premium for bearing those risks could produce most of the patterns we observe, at least those associated with the structural changes of 2020.

We examine this possibility using the Covid exposure measure of Hassan, Hollander, Van Lent, Schwedeler, and Tahoun (2023). **About the measure...** This measure is available starting in March 2020, so it is not possible to analyze Covid effects prior to that date. We therefore compute long-short portfolios separately for high and low Covid exposure firms only for the post-break sample, and we compare the returns of those portfolios to the pre-break long-short portfolios based on all firms. Analogous to Panel B of Figure 2, Figure **??** shows the magnitude of these breaks for stocks with high and low Covid exposure.

Implicit in this approach is the assumption that the risk of a pandemic like Covid was not contemplated by the market prior to March 2020. This is likely incorrect, in that the Covid was widespread in China for several months before. But as a characterization of the market's risk assessments over the vast majority of the pre-break sample, it may be more reasonable.

Panel A indicates that most of the differences between high and low Covid exposure portfolios are small, with all characteristics represented by dots close to and insignificantly different from the 45 degree line. Panels B and C show long and short legs separately. Among long legs, there are a few significant differences between high and low Covid exposures, but no clear pattern emerges across all the characteristics. For short legs, there is a slight tendency of high Covid exposure to be associated with somewhat less negative breaks for several characteristics, though the magnitudes of these differences are small.

We explore the role of Covid risk further by examining the role of industries. Given that Covid impacted some industries (e.g., airlines) much more than others (e.g., tech), industry dummy variables might capture a large fraction of the cross-sectional variation in Covid exposure, though they will almost certainly also pick up differences in retail trading unrelated to Covid.

Specifically, we run monthly cross-sectional regressions of stock retail ratios on 17 industry dummies, where industries are from Kenneth French's Data Library. The fitted values and residuals from each regression are interpreted, respectively, as the industry and industry-adjusted components of the retail ratio. Similar to previous analysis, we then form long-short portfolios using stocks from either the top of bottom half of the distribution of each component.

Panel A of Figure 5 shows pre-Covid average returns for long-short characteristic portfolios, where portfolios are formed either from stocks with high or low industry-level retail ratios. Panel B shows the corresponding magnitudes of the March 2020 structural breaks. Panels C and D are analogous, except that they instead use the industry-adjusted component of the stock retail ratio.

Panels A and B show a slight tendency for higher industry-level retail trading to have higher long-short returns and return breaks, though differences due to industry-level retail trading are mostly insignificant. In contrast, industry-adjusted retail trading has a large and highly significant relationship with both the pre-break average return and the magnitude of the break. In fact, results for industry-adjusted retail trading, shown in Panels C and D, are virtually identical to those based on raw retail trading, shown in Figure 2. Thus, to a close approximation, the relation between retail trading and option portfolio returns has nothing to do with industry exposure.

Of the two seismic shifts that occurred in 2020 – the rise of retail trading and the Covid pandemic – the former appears much more related to the increase in factor risk premia.

# 4 Retail trading and expected option returns

In the previous section, we showed that anomaly returns exhibit structural breaks, which coincide with periods of heightened retail trading activity. In this section, we further investigate this relationship. We start by analyzing how retail trading relates to various anomaly characteristics. Subsequently, we introduce a retail factor and establish that the structural breaks in anomaly returns can partially be explained by the structural break in the retail factor.

## 4.1 Retail preferences

Bryzgalova, Pavlova, and Sikorskaya (2023) document an upward trend in retail option trading in the period from November 2019 to June 2021 and find that retail trading losses are large and highly significant. Furthermore, they find that retail traders show a preference for more positively skewed positions, suggesting an attraction to lottery-like assets. However, using a different approach to classify retail trades,Bogousslavsky and Muravyev (2024) show little evidence of skewness-seeking behavior by option traders or even significant trading losses.

We extend the analysis of Bryzgalova, Pavlova, and Sikorskaya (2023) to examine how retail trading varies across firms, focusing specifically on the firm characteristics that drive average option returns. Specifically, we calculate the average stock and option retail ratios for long and short characteristic portfolios, in addition to their differences. These are reported in Table 3. Averages for the stock retail ratio are computed over the 2015 to 2021 sample period, while the sample for the option retail ratio starts in November 2019 due to data availability.

For the majority of anomalies, short positions are associated with significantly higher option and stock retail ratios compared to long positions. This observation aligns with the hypothesis that stocks experiencing high levels of retail trading are more likely to be overvalued. There are three notable exceptions: the IV term spread, option momentum, and the option bid-ask spread. We further analyze the stock and option retail ratios for all decile portfolios formed from these three characteristics (not tabulated). We find no clear relationship between these characteristics and retail ratios, suggesting that these anomalies are unlikely to be related to retail preferences.

Given that retail preferences are linked to option portfolio returns, it is natural to investigate whether those preferences exhibit structural changes alongside the option portfolio returns. To explore this, we calculate portfolio-level retail ratios of long and short legs in each month of our sample. We also examine an average high and average low portfolio that equally weights the assets in each of the 10 characteristic-based portfolios. Finally, we compute the return on an all-long portfolio that equally weights options on all firms.

We regress these portfolio-level retail ratios on a dummy variable with a value of 1 after March 2020. Similar to regression (2), the intercept represents the average retail ratio before March 2020, while the slope coefficient indicates the magnitude of the shift in the retail ratio after that date. We examine stock retail ratios only over the period from January 2015 to December 2021. An in earlier results, the absence of option retail ratios before November 2019 makes it difficult to measure structural changes in that variable.

Tabel 4 shows the estimated intercept and slope coefficients for these regressions. For the cross-sectional average portfolio, which holds long positions in the options on all firms, the slope coefficient is positive. This indicates an increasing fraction of retail trade across all stocks starting in the Covid period.

Among the 10 anomalies, seven have a negative intercept in the long-short regressions. This indicates a stronger retail preference, before March 2020, for stocks held in the short legs. More importantly, all but one portfolio exhibits a negative slope coefficient (with six out of the nine statistically significant), implying that the retail preference for short leg stocks tended to intensify with the beginning of the Covid period.

The long-short regressions don't tell us whether retail demand for short-leg stocks went up or whether it just went down less than long-leg stocks. We can distinguish these possibilities by examining the long and short legs separately, which we do in the last four columns of Table 4. We see that most anomalies exhibit positive slope coefficients for both legs, indicating an increased interest among retail investors after March 2020. However, the slope coefficients for the short legs are mostly larger (and more significant). This implies that retail investors increased their trading activity in stocks with lower future delta-hedged option returns.

## 4.2 A retail factor

Given the similar structural breaks between option portfolio returns and their corresponding retail ratios, it is worthwhile examining the returns of delta-hedged calls sorted by stock retail ratios. Specifically, we form decile portfolios based on lagged stock retail ratios from the previous month. Average returns of the delta-hedged calls within each decile are then calculated and presented, along with corresponding $t$-statistics, in Column 1 of Table 5.

We find that the return of options with the highest and lowest retail ratios are $-26$bps and $-104$bps per month, respectively. The difference in average return between the highest and lowest retail ratio groups is $-78$bps, which is statistically significant with a $t$-statistic of -8.16. The results confirm that options with high retail ratios tend to be more highly valued, leading to lower subsequent returns, while those with low retail ratios are cheaper, resulting in higher subsequent returns. Consequently, we define the retail factor as the return of a portfolio that is long the decile of delta-hedged calls with the lowest stock retail ratios and short the decile with the highest stock retail ratios.

If retail investors' preferences are the source of the structural breaks in long-short option portfolio returns, then a structural break should also be evident in the retail factor. To explore this, we apply regression (2) using the retail factor and decile portfolios sorted by retail ratios as the dependent variables. The intercept and slope coefficients of these regressions are reported in Columns 2 and 3 of Table 5.

The dramatic nature of the structural break in the retail factor is illustrated in Figure 6, which plots the time series of the retail factor. The figure indicates a structural break occurring after March 2020, a result confirmed by the Bai and Perron (1998, 2003) test. The synchronization of the structural breaks in retail factors and option portfolios provides further evidence of the link between structural breaks in option returns and retail trading.

If retail trading affects option anomalies, we would expect the retail factor to at least partially explain the level and break in those anomaly returns. We examine whether this is true by running the regression

$$R_{p,t} = \alpha_p + \beta_p I_t + \gamma_p f_{retail,t} + \epsilon_{p,t} \,. \tag{4}$$

The regression is similar to equation (2), but it adds the retail factor, $f_{retail,t}$, as another independent variable. The estimated coefficients and $t$-statistics of this regression for the ten anomaly portfolios, as well as the cross-sectional average portfolio, are shown in columns (1) to (3) of Table 6.

Turning first to the $\gamma_p$ coefficients in column (3), we observe positive values for seven out of the ten portfolios, all statistically significant. Positivity indicates that the long side of the anomaly portfolio performs better when options held by retail traders lose. Anomaly portfolios are, in other words, a bet against retail traders.

The $\beta_p$ coefficients in column (2), measuring the size of the structural break after controlling for the retail factor, are still mostly positive. Thus, the retail factor does not completely explain the structural breaks in long-short returns. That said, the average $\beta_p$ in this table, 0.053, is about half of the average estimate from Table 2, which did not include the retail factor. Thus, retail trading explains a large fraction of the post-March 2020 shift in returns. A slightly smaller reduction is observed for the average $\alpha_p$, meaning that the retail trading factor also explains part of the pre-March 2020 average returns.

To further investigate the effect of the retail factor on individual anomalies, we plot the intercept and slope coefficients of the breakpoint dummy from regressions 2 and 4 for all anomalies. The scatter plots are presented in Figure 7. In Panel A, each dot represents an anomaly portfolio, where the x- and y-axes correspond to the intercepts from regressions (2) and (4), respectively. The color of each dot indicates the significance level of the difference in intercepts between the two regressions. Similarly, Panel B displays the scatter plot for the slope coefficients.[5]

In both panels, 6-7 out of 10 dots fall significantly below the 45-degree line, suggesting

[5]We use the Hausman test to test significance of the difference between the intercepts and coefficients from equation (2) and (4). Let $\mathbf{a}_2 \equiv (\alpha_{i,2}, \beta_{i,2})$ denote an intercept and slope from regression (2) and let $\mathbf{a}_4$ be the corresponding parameters from regression (4). The following statistic is calculated:

$$(\mathbf{a}_2 - \mathbf{a}_4)^\top (\mathrm{Var}(\mathbf{a}_2) - \mathrm{Var}(\mathbf{a}_4))^{-1} (\mathbf{a}_2 - \mathbf{a}_4) \quad (5)$$

Here, $\mathrm{Var}(\mathbf{a}_2)$ and $\mathrm{Var}(\mathbf{a}_4)$ are the covariance matrices of the $\alpha$ and $\beta$ parameters from regressions (2) and (4), respectively. The statistic in equation (5) follows a $\chi^2$ distribution with two degrees of freedom.

that the retail factor accounts for a large fraction of the the returns and structural breaks of most anomalies. Exceptions include the IV term spread, option momentum, and volatility risk premium, which again appear unrelated to retail pressures.

# 5 What drives retail interest?

In the previous sections, we showed that retail trading is strongly related to average option returns. In this section, we aim to examine the mechanisms of retail investor behavior and their impact on those returns. We investigate three possible channels: lottery preferences, extrapolative beliefs, and attention bias.

The impact of investors' lottery preferences on option returns has been documented by Boyer and Vorkink (2014), Byun and Kim (2016), and Liu, Wang, Yu, and Zhao (2020). These studies suggest that call options are overvalued because the pursuit of large payoff gambles leads to speculative overinvesting in options. It seems likely that the significant increase in retail investors since 2020 has exacerbated this effect.

Extrapolative beliefs, as discussed by Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998), suggest that investors disproportionately weigh recent price patterns over long-term historical trends. When investors observe price increases over a period of time, they are more likely to continue purchasing options based on this recent trend, leading to overvaluation. Atmaz (2022) constructs a model in which the investors' extrapolation influences their expectation for future stock returns and volatility. A negative shock to stock returns is associated with an upward bias in expectations about future stock volatility, potentially raising retail interest and increasing option prices.

Lastly, the relationship between investor attention and option returns has been explored by Choy and Wei (2023), who show that retail traders tend to trade more in the stocks with extreme past returns, both positive and negative. Cao, Li, Zhan, and Zhou (2022) show option trading imbalances are influenced by sentiment from retail investors. During the Covid-19 period, it is possible that a rise in the attention that retail traders pay to some firms has resulted in their options becoming overpriced.

## 5.1 Proxies for retail interest determinants

To distinguish between these mechanisms, we construct measures associated with lottery preference, extrapolation beliefs, and attention. We then examine whether these measures correlate with retail investors' preferences as well as the structural breaks in anomaly returns. This analysis allows us to identify the specific behaviors driving the observed effects on option portfolio returns.

We use five different proxies for lottery preferences. The first is the expected idiosyncratic skewness measure of Boyer and Vorkink (2014), which projects realized idiosyncratic skewness on lagged firm characteristics to produce a skewness forecast. Next is the jackpot probability of Conrad, Kapadia, and Xing (2014), which measures the likelihood of an annual firm return greater than 100%. Our third measure is the maximum daily stock return from the previous month, which Bali, Cakici, and Whitelaw (2011) argue is an attractor to skewness-seeking investors. We also include stock price, an easily observed variable that Kumar (2009) finds to be a good predictor of higher idiosyncratic volatility. Lastly, we include idiosyncratic volatility itself from the four-factor model of Carhart (1997). We compute each of these five lottery measures on the third Thursday of the month, one day before portfolio formation. Additional details for all these measures are in Appendix C.

Our proxy for extrapolation is the lagged one-month return on the underlying stock.

**Robustness to longer horizons.**

As a measure of attention, we follow Da, Engelberg, and Gao (2011) and use Google search volume, which they find to be a superior measure of attention by retail investors.

We depart from Choy and Wei (2023), who use extreme past returns as an attention proxy, given that extreme past returns should be larger when stock volatility is high, making them also interpretable as a lottery payoff measure. Moreover, as Da, Engelberg, and Gao (2011) argue, Google search volume is a good proxy for the attention of retail investors specifically.

However, we differ from Da, Engelberg, and Gao (2011) by examining cross-sectional variation in the levels rather than growth rates of attention, which requires that we rescale the search volume data provided on the Google Trends website. This is because the week with the highest search volume for the term queried is normalized to 100, with the remaining weekly search volumes reported as values relative to this maximum.

To ensure cross-sectional comparability of search volumes, we perform simulteneous searches that include both a given stock and a benchmark firm, taken as CPS (Cooper-Standard Holdings Inc.).[6] When doing so, the maximum weekly search volume across both firms queried is set to 100, with the remaining volumes scaled accordingly. Because the same benchmark firm is included in each query, we are able to adjust all non-benchmark firms to be cross-sectionally comparable with the benchmark.

Our monthly attention measure is the sum of the most recent four weeks of search volumes prior to portfolio formation. Additionally, when retrieving Google search volume data, we use the historical ticker symbols of each stock. We also exclude ticker symbols with multiple meanings, such as "GPS" and "LA," to ensure the accuracy and relevance of the search results.

## 5.2 Explaining retail trading

We begin by examining whether stock retail preference is associated with lottery preferences, trend, and/or attention. To this end, we perform Fama-MacBeth regressions using the stock or option retail ratio for each firm as the dependent variable, with proxies for lottery

[6] We choose CPS because it is close to the median firm in market cap during our sample and has close to the median level of Google search volume.

preferences, trend, and attention serving as independent variables.

The results of our analysis are presented in Table 7. Panel A examines stock retail ratios, with univariate regressions on the left and multiple regressions on the right. Note that all variables are standardized using a different cross-sectional mean and standard deviation in each period, so coefficients in the univariate regressions represent average cross-sectional correlations between the independent and dependent variables.

For all five lottery features, the average correlation coefficient is nearly 40% in absolute value or larger, with all $t$-statistics above 20, indicating strong a strong retail preference for stocks with lottery-like payoffs. In contrast, our trend and attention measures are nearly uncorrelated (6% and 5%, respectively) with retail trading.

The right side of Panel A runs a horse race between the different lottery proxies and the trend and attention variables. Overall, multiple regression betas are similar to univariate betas, and the coefficients for lottery features continue dominate the others. Furthermore, the addition of trend and attention variables to any lottery proxy improves the R-squared value by no more than a few percentage points relative to the univariate regressions with lottery proxies only. These findings underscore that a preference for lottery-like features appears to be the primary driver of retail preferences.

In Panel B, we repeat this analysis using option retail ratios. In the univariate regressions, we see mostly smaller coefficients than observed for stock retail ratios, but overall the evidence is consistent with those results. In both univariate and multiple regressions, lottery proxies are much more predictive of option retail ratios than either trend or attention.

## 5.3 Lottery characteristics and factor returns

In the previous section, we showed that lottery characteristics are associated with retail preferences. Given the correlation between retail activity and option characteristics, it is natural to close the loop by examining the relationship between lottery and option characteristics.

To this end, we again examine deciles based on the option characteristics used to construct option anomaly portfolios. We then calculate the average lottery characteristics for both the short and long legs. We report these values and their differences in Table 8.

For example, the first three columns of the first row show that the expected idiosyncratic skewness of stocks in the low idiosyncratic volatility decile (which is held long) is essentially zero, while the average expected idiosyncratic skewness in the high decile (held short) is highly positive at 1.68. The difference between these values is highly significant. Remarkably, this pattern holds for all ten anomaly characteristics: the options held long have higher average expected idiosyncratic skewness than the options held short.

Results for the other lottery proxies are only slightly less consistent. All anomaly portfolios have higher jackpot probabilities and lower stock prices on the short side Eight out of ten portfolios have larger average maximum returns on their short legs, the same eight also having higher idiosyncratic volatility in their shorts.

## 5.4 A lottery factor

With all anomaly characteristics showing at least some relation to lottery proxies, a systematic exploration of the relation between the returns to anomalies and lottery proxies is warranted. To do so, we form deciles from each lottery characteristic and construct delta-hedged returns for each. We then compute long-short lottery factors by holding the deciles with low lottery characteristics long and the deciles with high lottery characteristics short.

Panels A through E of Figure 8 show the time series of returns for each of the five lottery factors. The graphs also identify any structural breaks found using the Bai and Perron (1998) test.

For all five lottery portfolios, a pronounced structural break is again identified near the beginning of 2020. Bai and Perron tests show that these structural breaks predominantly occur in February 2020, with the exception of the max return portfolio, for which the break is observed three months later.

Panel F of the same figure shows returns on a overall lottery factor, constructed as the first principal component of all five lottery characteristic portfolios. A similar structural break is identified in February 2020. All realizations of this factor after that point, through the end of 2021, are positive.

Similar to earlier analysis, we examine whether the lottery factor can explain the structural breaks in the anomaly portfolios. To this end, as in Section 3.2, we regress the returns of a long-short portfolio on a time dummy representing the break period and the lottery factor:

$$R_{p,t} = \alpha_p + \beta_p I_t + \gamma_p f_{lottery,t} + \epsilon_{p,t}\,. \tag{6}$$

Here, $R_{p,t}$ is the return for portfolio $p$ at month $t$, $I_t$ is a month dummy with value 1 after March 2020, and $f_{lottery,t}$ is the PC-based lottery factor described above. The estimated coefficients and their $t$-statistics are presented in Table 9.

For five out of the ten anomaly portfolios, the slope coefficient for the structural breaks, $\beta_p$, becomes insignificant. For the portfolio formed on the basis of idiosyncratic volatility, the $\beta_p$ coefficient flips sign and turns negative. For the remaining four portfolios, the $\beta_p$ coefficients are reduced, accompanied by much lower $t$-ratios (with the exceptions of the volatility risk premium and option momentum).

Table 9 also includes a regression for the average long-short anomaly portfolio. The size of the structural break not explained by the lottery factor is about 27 bps. While this coefficient is significant, it is far smaller than the corresponding value of 103 bps from Table 2, which did not control for the lottery factor. Thus, the structural breaks observed in most option anomalies can largely be attributed to the changing returns to lottery seeking portfolios.

To a lesser extent, the lottery factor also explains average returns before the breakpoint. From Table 2, the average pre-March 2020 return across all ten option anomalies was 70 bps. per month. In Table 9, controlling for the lottery factor, it is 32 bps. Thus, while the lottery factor explains average returns generally to a degree, it is more successful in explaining the post-March 2020 break.

It is important to acknowledge the mechanical nature of some of the results in Table 9. The lottery factor is constructed, in part, using returns to a portfolio formed on expected idiosyncratic skewness. It is therefore not surprising that it does well in explaining the returns to the closely-related risk-neutral skewness factor. While the factor has explanatory power for some anomalies, such as the option bid-ask spread, that are not as mechanically related to the lottery factor, the lottery factor's success must be interpreted with this caveat.

In part to address this concern, the last row of Table 9 examines the retail factor from Section 4.2 as an additional dependent variable. The retail factor is not constructed from any risk measure, so its relation to the lottery factor is not so automatic.

We find that controlling for the lottery factor renders both the constant and the breakpoint parameter $\beta_p$ insignificant. Thus, the Covid-related increase in the prices of options on stocks favored by retail investors can be attributed to the lottery characteristics of those stocks.

# 6 Conclusions

Substantial effort has been made to understand the effect of the Covid lockdown on financial markets, but most work to date has focused either on the stock market (e.g., Welch 2022; Greenwood, Laarits, and Wurgler 2023) or Bitcoin (e.g., Divakaruni and Zimmerman 2024). While some of this work focuses on the impact of retail trading on asset prices (e.g., Barber, Huang, Odean, and Schwarz 2022), the demonstrated impact is limited to a small number of stocks experiencing extreme retail attention (Barber, Huang, Odean, and Schwarz 2022) or to the periods immediately following Covid stimulus payments (Greenwood, Laarits, and Wurgler 2023). There is little evidence of any broad and sustained impact from changes in retail trader behavior.

Because the Covid pandemic coincided with the rise of retail option investing (Bryzgalova, Pavlova, and Sikorskaya (2023)), it is natural to consider the options market as an alternative venue for such an impact. When we do so, we find large and persistent changes in option factor risk premia that exactly coincide with the beginning of the Covid lockdown. These changes in risk premia are much larger among options more likely to be held by retail investors and are unrelated to Covid or industry exposures.

In almost every case, we find that retail investors are drawn to options held short in the various anomaly portfolios, trading the options with the lowest average returns. This is true before the pandemic, but the pattern intensifies significantly starting around March 2020. A factor constructed to represent retail trading explains about half of the magnitude of the breakpoints in anomaly returns.

We analyze the determinants of retail activity, focusing on lottery preferences, attention, and extrapolation. Though we find modest support for attention and extrapolation, various proxies for lottery preferences are far more able to explain retail trading both in stocks and options. Furthermore, lottery characteristics are higher for the short sides of the anomaly portfolios in almost every case.

We construct a lottery factor that explains the majority of the structural break in anomaly returns. Moreover, it explains the large structural break in the retail factor, suggesting that the pricing effects of higher option demand by retail investors occur as the result of lottery chasing behavior.

Our study highlights the importance of time-varying risk premia in options markets. It suggests, however, that return predictability may best be understood by focusing on quantity rather than price measures. In addition, the presence of discrete changes in option risk premia raises the question of whether standard measures of option factor momentum (e.g., Käfer, Mörke, and Wiest 2024) are meaningful.

The options market is now comparable to the stock market in trading volume. Furthermore, it is a market that is now nearly 50% retail (Poser 2023), as opposed to around 25% for the stock market (Einhorn, Fisch, Ricci, Le, and Sautter 2023). Those facts, combined with the strength of our own findings, suggest that the options market may be the more fruitful setting in which to explore the rising impact of retail traders.

# A Additional details on data construction

The datasets from **OptionMetrics** are linked to **CRSP** using a linkage file provided by WRDS. This ensures that each *secid* (security identifier) from **OptionMetrics** in our sample corresponds uniquely to a **CRSP** *PERMNO* (permanent number) on the initiation day of delta-hedged portfolios. Furthermore, we include only those options whose underlying *PERMNO* represents common stocks traded on the NYSE, AMEX, or the Nasdaq Stock MarketSM. We verify that each *secid* from **OptionMetrics** is associated with only one *PERMNO* at the start of our analysis period, and we attach lagged characteristics from **CRSP** to the *secid* using the matched *PERMNO*.

The *secid* is associated with its option retail trading data and stock trading data through the historical *Ticker*. Options with specified strike prices, expiration dates, option types (call or put), and historical tickers can be matched to the relevant trading data for those specific options on the given dates.

After linking the option returns to their PERMNO IDs, we connect them to their corresponding GVKEY codes provided by Compustat, ensuring the validity of these linkages when forming the delta-hedged portfolios. With the GVKEYs identified, we then obtain the firm-level characteristics tangibility and sales, which are later used to calculate Jackpot characteristics.

# B Construction of firm characteristics

- IV: The implied volatility for the call options included in the delta-hedged portfolios is recorded on the third Thursday, just prior to the establishment of the delta-hedged portfolios. This implied volatility is obtained from the option price file.

- Qvar: Risk-neutral variance. It is calculated from the option prices from the volatility surface file following the steps below: We follow Bakshi, Kapadia, and Madan (2003) to firstly calculate the following three equations using the option prices observed on the third Thursday of each month (just before we form the delta-hedged portfolios) with options having a time to maturity of 30 days.

$$V = \sum_{\delta_i} \frac{2C_{\delta_i} \cdot \left(\ln\left(\frac{S}{K_{\delta_i}}\right) + 1\right)}{K_{\delta_i}^2} \Delta K_{\delta_i} + \frac{2P_{\delta_i} \cdot \left(\ln\left(\frac{S}{K_{\delta_i}}\right) + 1\right)}{K_{\delta_i}^2} \Delta K_{\delta_i},$$

$$W = \sum_{\delta_i} \frac{-3C_{\delta_i} \cdot \ln\left(\frac{S}{K_{\delta_i}}\right) \cdot \left(\ln\left(\frac{S}{K_{\delta_i}}\right) + 2\right)}{K_{\delta_i}^2} \Delta K_{\delta_i} + \frac{-3P_{\delta_i} \cdot \ln\left(\frac{S}{K_{\delta_i}}\right) \cdot \left(\ln\left(\frac{S}{K_{\delta_i}}\right) + 2\right)}{K_{\delta_i}^2} \Delta K_{\delta_i},$$

$$X = \sum_{\delta_i} \frac{4C_{\delta_i} \cdot \ln\left(\frac{S}{K_{\delta_i}}\right)^2 \cdot \left(3 + \ln\left(\frac{S}{K_{\delta_i}}\right)\right)}{K_{\delta_i}^2} \Delta K_{\delta_i} + \frac{4P_{\delta_i} \cdot \ln\left(\frac{S}{K_{\delta_i}}\right)^2 \cdot \left(3 + \ln\left(\frac{S}{K_{\delta_i}}\right)\right)}{K_{\delta_i}^2} \Delta K_{\delta_i}.$$

  Here $\delta_i$ stands for the -i-th option's sensitivity to the directional movement of the stock prices, $K_{\delta_i}$ ($C_{\delta_i}$) is the strike price (call option price) of the option with a delta of $\delta_i$ and a time to maturity of 30 days.

  The volatility surface file provides option prices with standard delta and time-to-maturity, with the change in $\delta$ for 2 consecutive options at 0.05.

For call options, we use options with

$$\delta_i \in [0.1, 0.45], \quad \Delta K_{\delta_i} = K_{\delta_i} - K_{\delta_{i+1}} \text{ for } \delta_i < 0.45,$$

$$\text{and } \Delta K_{\delta_i} = K_{(\delta_i=0.45)} - S \text{ when } \delta_i = 0.45.$$

For put options, we use

$$\delta_i \in [-0.45, -0.1], \quad \Delta K_{\delta_i} = K_{\delta_{i-1}} - K_{\delta_i} \text{ for } \delta_i > -0.45,$$

$$\Delta K_{\delta_i} = -K_{(\delta_i=-0.45)} + S \text{ when } \delta_i = -0.45.$$

Then we calculate

$$\begin{aligned} Q_{\text{var}} &= \frac{e^{rT}V - \mu^2}{1.5}, \\ Q_{\text{skew}} &= \frac{e^{rT}W - 3\mu e^{rT}V + 2\mu^3}{(e^{rT}V - \mu^2)^{1.5}}, \\ Q_{\text{kurt}} &= \frac{e^{rT}X - 4\mu e^{rT}W + 6e^{rT}\mu^2 V - 3\mu^4}{(e^{rT}V - \mu^2)^2}, \end{aligned}$$

with

$$\mu = e^{rT} - 1 - \frac{e^{rT}}{2}V - \frac{e^{rT}}{6}W - \frac{e^{rT}}{24}X.$$

Here r is the risk-free rate, calculated from ICE IBA LIBOR rates and settlement prices of CME Eurodollar futures. and $\tau$ is the time to maturity, which is 30 days

- Qskew: Risk-neutral skewness is calculated following the steps above

- IV term spread: Implied volatility term spread is calculated as

$$\text{IV-Term-Spread} = IV_{30} - IV_{365}$$

where $IV_{30}$ ($IV_{365}$) is the average of implied volatility of a call option with a delta of 0.5 and a put option with a delta of -0.5 for the same underlying stock from the volatility surface file. Both call and put options have a time-to-maturity of 30 (365) days and are observed on the third thursday this month (just the day before we form the delta-hedged portfolios).

- Mcap: Stock market capitalization is calculated as log(stock price× outstanding shares), with both stock price and outstanding shares observed on the third thursday. The stock price used here is the closing price of the underlying stock on the third Thursday.

- Opt spread: Option bid-ask-spread. It is calculated as

$$Opt\text{-}Spread = \frac{\text{Best}_{\text{offer}} - \text{Best}_{\text{bid}}}{\text{Best}_{\text{offer}} + \text{Best}_{\text{bid}}} \times 2.$$

  Here $Best_{bid}$ ($Best_{offer}$) is the close bid (ask) price of the options used in the delta-hedged portfolios and is observed on the third thursday this month (just before we form the delta-hedged portfolios).

- HVIV: one-year historical volatility minus the implied volatility of 30-day at-the-money options. The historical volatility is calculated as the standard deviation of the logarithm of close-to-close daily total returns over the past year and ends on the third thursday. The implied volatility is the average of the implied volatilities of a call option with a delta of 0.5 and a put option with a delta of -0.5, both maturing in 30 days. These implied volatilities are obtained from the volatility surface file. Both historical and implied volatilities are observed on the third Thursday.

- Opt mom: We construct One-year option momentum as the equal-weighted average of the monthly returns of at-the-money delta-hedged option portfolios for a specific underlying stock. This calculation requires at least 8 non-missing monthly observations. It is important to note that for the calculation of option momentum (Opt mom), there is no requirement for the options included in the delta-hedged portfolios to have positive open interest or trading volume on the initiation day

- Ivol: Idiosyncratic volatility. To calculate the idiosyncratic volatility, we apply the Fama-French 4-factor model to the daily stock returns for the last year (ending on the third thursday this month), requiring a minimum number of non-missing daily return observations of 126 (half of a year). Next the idiosyncratic volatility is calculated as the standard deviation of the residuals in the regression.

# C Lottery proxies

We follow Boyer and Vorkink (2014) to estimate expected idiosyncratic skewness with the steps below:

Let the investment horizon over which investors are hoping to experience an extreme positive outcome be $T$ months, let $S(t)$ denote the set of trading days from the first day of month $t-\tau+1$ through the end of month $t$, and let $N(t)$ denote the number of days in this set. Let $\epsilon_{i,d}$ be the regression residual using the Fama and French (1993) three-factor model on day $d$ for firm $i$, where the regression coefficients that define this residual are estimated using daily data for days in $S(t)$. In addition, let $iv_{i,t}$ and $is_{i,t}$ denote historical estimates of idiosyncratic volatility and skewness (respectively) for firm $i$ using daily data for all days in S(t), and $iv_{i,t} = \sum_{d\in S(t)}(\epsilon_{i,d}^2)/N(t)])^{0.5}$, and $is_{i,t} = \sum_{d\in S(t)} \frac{\epsilon_{i,d}^3}{N(t)iv_{i,t}}$

For $t$ from January 1991 through December 2021, and $T = 60$ months, with common stocks listed on the three major exchanges, we run the following cross-sectional regression for each month:

$$is_{i,t} = \beta_{0,t} + \beta_{1,t} is_{i,t-\tau} + \beta_{2,t} iv_{i,t-\tau} + \lambda^T X_{i,t-T} + \epsilon_{i,t} \tag{7}$$

Here, $X_{i,t-T}$ is a vector of additional firm-specific variables observable at the end of month

$t-T$. The observations used in this regression must have at least 10 years of data from $t-2\times T+1$ to $t$ and the estimated coefficients use only information known before time $t$. With the estimated coefficients, Expected idiosyncratic skewness is calculated as

$$E_t[is_{i,t+T}] = (\hat{\beta_{0,t}}) + (\hat{\beta_{1,t}})is_{(i,t} + (\hat{\beta_{2,t}})iv_{i,t} + (\hat{\lambda_t})x_{i,t} \tag{8}$$

$E_t[is_{i,t+\tau}]$ is a forward-looking variable and uses only information available at the end of time $t$. we can estimate $E_t[is_{i,t+\tau}]$ even when the firm $i$ does not have realized idiosyncratic skewness for this period, as the calculation of realized idiosyncratic skewness requires data for the following five years, while $E_t[is_{i,t+\tau}]$ accounts for information through time $t$. Also, as $E_t[is_{i,t+\tau}]$ is estimated at the end of month $t$, but the delta-hedged portfolios are constructed on the third Friday of each month, we use $E_t[is_{i,t+\tau}]$ observed in the end of month $t$ for delta-hedged portfolios formed on the third Friday of month $t+1$.

We follow Conrad, Kapadia, and Xing (2014) to define jackpot as a binary variable, which is equal to one if the log return is greater than 100% over the next year for the underlying stock. We then run the following logit model with a panel regression using a 20-year rolling window:

$$P_{t-1}[Jackpot_{i,t} = 1] = \frac{exp^{a+btimesX_{i,t-1}}}{1+exp^{a+bX_{i,t-1}}} \tag{9}$$

Here, $Jackpot_{i,t}$ is a dummy variable that equals one if the firm's log return in the next 12 month period (from $t$ to $t+1$) is larger than 100%, and $X_{i,t-1}$ is a vector of independent variables known at time $t-1$. We begin by estimating the parameters of a baseline logit model using at least 20 years of historical data and then construct out-of-sample estimates of jackpot probabilities. We re-estimate this model once a year (at the end of June), to avoid the use of overlapping returns.

The independent variables include the stock's log return over the last 12 months (RET12), volatility (STDEV) and skewness (SKEW) of daily log returns over the past three months, detrended stock turnover (TURN = six month volume / shares outstanding minus 18 month volume / shares outstanding), size (SIZE: log market capitalization), firm age (AGE: number of years since first appearance on CRSP), asset tangibility (TANG: Gross Property Plant and Equipment / Total Assets), and sales growth (SALESGRTH) over the prior year. In the process to estimate the regression coefficient, both dependent variables and independent variables are required to be non-missing. After estimating the parameters at the end of the June of the $n^{th}$ year, the independent variables observed in June of year $n+1$ are used to predict the Jackpot dependent variable for the following one-year period as follows:

$$\frac{exp^{\hat{a}+\hat{b}times X_{i,n+1.5}}}{1+exp^{\hat{a}+\hat{b}\times X_{n+1.5}}} \tag{10}$$

Here, $X_{n+1.5}$ signifies that the we use the most up-to-date independent variables, observed at the middle of year $n+1$ (June), and $\hat{a}$ and $\hat{b}$ are also estimated as of the same time. As a result, we do not have any look-ahead bias in the Jackpot forecasts.

The maximum daily stock return is calculated from the third Friday of one month to the third Thursday of the next month, one day prior to portfolio formation. Brunnermeier, Gollier, and Parker (2007) show a model in which agents optimally choose to distort their beliefs about future probabilities in order to maximize current utility. Critical to these interpretations, stocks with extreme positive returns in a given month are also seen as more likely to exhibit this phenomenon in the future. Stocks with higher maximum daily stock returns are therefore viewed as lotteries.

Stocks with low prices are shown to have higher idiosyncratic volatility and considered to have greater potential to have extreme returns, which is considered as lottery by the retail traders by Kumar (2009). The stock price is the closing price of the underlying stocks on the third Thursday of the month, one day before portfolio formation.

Finally, to calculate idiosyncratic volatility, we apply the Fama-French 4-factor model to daily stock returns over the past year (again ending on the third Thursday of the month).

We require a minimum number of 126 non-missing daily return observations. Idiosyncratic volatility is calculated as the standard deviation of the residuals of this regression.

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Table 1: **Breakpoint Timing for Option Portfolios**

This table shows the timing of multiple breakpoints for the option portfolios identified by the Bai and Perron (1998, 2003) test. The option portfolios are constructed from delta-hedged at-the-money call options defined following equation (1). The long-short portfolios are based on firm characteristics defined in Section 2.3. An equally-weighted average delta-hedged return and a delta-hedged portfolio return for the S&P 500 Index are also examined. The sample period ranges from January 2015 to November 2022.

| | **Timing for Breakpoints** | |
|---|---|---|
| | **First Breakpoint** | **Second Breakpoint** |
| **Implied Volatility** | 2020(3) | 2021(11) |
| **Risk-neutral Variance** | 2020(3) | 2021(11) |
| **Risk-neutral Skewness** | 2020(3) | 2021(11) |
| **Risk-neutral Kurtosis** | 2020(3) | 2021(11) |
| **IV Term Spread** | | |
| **Market Cap** | 2020(3) | |
| **Option Bid-Ask Spread** | 2020(3) | |
| **Volatility Risk Premium** | 2020(3) | |
| **Option Momentum** | 2020(10) | |
| **Idiosyncratic Volatility** | 2020(3) | 2021(10) |
| **SPX** | | |
| **Cross-Sectional Average** | 2020(4) | |

Table 2: **Magnitude of Structural Breaks**
The first two columns present intercepts and slope coefficients from the regression

$$R_{p,t} = \alpha_p + \beta_p I_t + \epsilon_{p,t} ,$$

where $R_{p,t}$ is the return for anomaly portfolio $p$ at month $t$ and $I_t$ is a monthly dummy with value 1 after March 2020. Columns 3 to 6 present results for the same regressions with long legs and short legs separately. Columns 7 to 9 present the results for the regression

$$R_{p,t} = \alpha_p + \beta_p I_t + \gamma_p CS_t + \epsilon_{p,t} ,$$

where $CS_t$ is the return for the equal-weighted portfolio of delta-hedged call returns. The intercept of the regression represents the average portfolio return before the structural break, and the slope coefficient indicates the magnitude of the structure break. "Average H-L" is the equal-weighted average of all the long-short portfolios' returns. An equal-weighted portfolio of all delta-hedged calls and a delta-hedged portfolio for the S&P 500 Index are also examined. The sample period ranges from January 2015 to December 2021. Newey-West standard errors with three lags are applied to calculate the $t$-statistics.

| | **Long-Short return** | | **Long-Leg return** | | **Short-Leg return** | | **Adjusted by CS Average** | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | $\alpha_p$ | $\beta_p$ | $\alpha_p$ | $\beta_p$ | $\alpha_p$ | $\beta_p$ | $\alpha_p$ | $\beta_p$ | $\gamma_p$ |
| **Implied Volatility** | 0.0105 | 0.0179 | 0.0004 | -0.0045 | -0.0101 | -0.0223 | 0.0096 | 0.0131 | 0.6191 |
| | (9.45) | (8.58) | (0.58) | (-4.66) | (-7.63) | (-9.93) | (8.35) | (6.70) | (4.89) |
| **Risk-neutral Variance** | 0.0099 | 0.0121 | 0.0004 | -0.0041 | -0.0095 | -0.0162 | 0.0090 | 0.0076 | 0.5814 |
| | (9.15) | (6.23) | (0.59) | (-3.83) | (-7.46) | (-7.30) | (8.28) | (4.15) | (6.17) |
| **Risk-neutral Skewness** | 0.0058 | 0.0113 | -0.0008 | -0.0053 | -0.0067 | -0.0165 | 0.0052 | 0.0083 | 0.3879 |
| | (6.86) | (6.62) | (-1.00) | (-4.44) | (-5.35) | (-7.80) | (6.11) | (4.80) | (3.14) |
| **Risk-neutral Kurtosis** | 0.0075 | 0.0135 | -0.0006 | -0.0049 | -0.0081 | -0.0184 | 0.0069 | 0.0106 | 0.3727 |
| | (8.12) | (6.75) | (-0.68) | (-4.00) | (-6.76) | (-7.35) | (6.99) | (5.38) | (2.84) |
| **IV Term Spread** | 0.0043 | 0.0012 | -0.0023 | -0.0111 | -0.0067 | -0.0123 | 0.0042 | 0.0005 | 0.0912 |
| | (4.98) | (0.83) | (-2.34) | (-7.75) | (-7.52) | (-5.95) | (4.49) | (0.36) | (0.97) |
| **Market Cap** | 0.0062 | 0.0156 | 0.0003 | -0.0032 | -0.0058 | -0.0188 | 0.0054 | 0.0117 | 0.5084 |
| | (6.55) | (8.17) | (0.42) | (-2.04) | (-5.01) | (-10.14) | (5.96) | (4.44) | (4.55) |
| **Option Bid-Ask Spread** | 0.0049 | 0.0063 | 0.0002 | -0.0055 | -0.0048 | -0.0118 | 0.0047 | 0.0052 | 0.1497 |
| | (7.18) | (5.86) | (0.27) | (-3.31) | (-4.96) | (-7.87) | (6.83) | (2.91) | (1.08) |
| **Volatility Risk Premium** | 0.0070 | 0.0079 | -0.0018 | -0.0085 | -0.0088 | -0.0164 | 0.0071 | 0.0082 | -0.0434 |
| | (6.64) | (3.41) | (-1.63) | (-4.78) | (-8.71) | (-7.64) | (6.01) | (3.27) | (-0.22) |
| **Option Momentum** | 0.0065 | 0.0059 | -0.0007 | -0.0047 | -0.0072 | -0.0106 | 0.0063 | 0.0049 | 0.1297 |
| | (9.23) | (4.41) | (-0.77) | (-2.59) | (-6.01) | (-7.15) | (7.81) | (2.36) | (0.59) |
| **Idiosyncratic Volatility** | 0.0075 | 0.0119 | 0.0004 | -0.0040 | -0.0070 | -0.0159 | 0.0066 | 0.0075 | 0.5684 |
| | (5.76) | (5.41) | (0.55) | (-3.43) | (-5.43) | (-7.16) | (4.78) | (3.44) | (5.64) |
| **Average H-L** | 0.0070 | 0.0103 | -0.0005 | -0.0056 | -0.0075 | -0.0159 | 0.0060 | 0.0078 | 0.3875 |
| | (11.38) | (8.80) | (-0.61) | (-4.62) | (-7.16) | (-8.72) | (9.07) | (5.98) | (8.47) |
| **Cross-Sectional Average** | | | -0.0015 | -0.0077 | | | | | |
| | | | (-1.87) | (-5.82) | | | | | |
| **S\&P 500** | | | 0.0007 | -0.0040 | | | | | |
| | | | (1.10) | (-3.27) | | | | | |

Table 3: **Retail Ratios for Option Anomalies**

Using decile sorts on various option anomaly characteristics, we compute average option and stock retail ratios for options held in the long and short legs of the anomaly portfolio. The table reports the time series means of these ratios, as well as the differences between them, with *t*-statistics in parentheses. Data for stock retail ratios ranges from January 2015 to December 2021, while data for option retail ratios is from November 2019 to December 2021. We use Newey-West standard errors with three lags.

| | **Option Retail Ratio** | | | **Stock Retail Ratio** | | |
|---|---|---|---|---|---|---|
| | **Short Leg** | **Long Leg** | **Long - Short** | **Short Leg** | **Long Leg** | **Long - Short** |
| **Implied Volatility** | 0.22 | 0.13 | -0.09 | 0.14 | 0.05 | -0.09 |
| | (20.10) | (50.95) | (-8.71) | (47.28) | (62.20) | (-29.49) |
| **Risk-Neutral Variance** | 0.20 | 0.12 | -0.08 | 0.13 | 0.05 | -0.08 |
| | (21.07) | (39.89) | (-8.09) | (63.49) | (57.30) | (-31.04) |
| **Risk-Neutral Skewness** | 0.23 | 0.15 | -0.08 | 0.14 | 0.04 | -0.09 |
| | (23.07) | (46.64) | (-9.01) | (68.61) | (59.92) | (-52.50) |
| **Risk-Neutral Kurtosis** | 0.23 | 0.14 | -0.08 | 0.14 | 0.04 | -0.10 |
| | (22.10) | (44.95) | (-8.81) | (57.84) | (70.55) | (-45.22) |
| **IV Term Spread** | 0.18 | 0.18 | 0.00 | 0.09 | 0.09 | 0.00 |
| | (27.19) | (25.65) | (0.48) | (33.09) | (52.64) | (-2.03) |
| **Market Cap** | 0.23 | 0.12 | -0.11 | 0.14 | 0.07 | -0.07 |
| | (17.21) | (31.82) | (-7.56) | (55.89) | (54.94) | (-27.95) |
| **Option Bid-Ask Spread** | 0.16 | 0.16 | 0.00 | 0.08 | 0.09 | 0.01 |
| | (28.05) | (25.99) | (-0.13) | (59.93) | (26.27) | (3.34) |
| **HV - IV** | 0.20 | 0.17 | -0.02 | 0.10 | 0.10 | -0.01 |
| | (23.73) | (19.61) | (-3.40) | (32.79) | (38.73) | (-1.73) |
| **Option Momentum** | 0.17 | 0.15 | -0.01 | 0.08 | 0.09 | 0.00 |
| | (24.47) | (32.93) | (-2.26) | (82.74) | (63.77) | (2.62) |
| **Idiosyncratic Volatility** | 0.20 | 0.13 | -0.06 | 0.12 | 0.05 | -0.08 |
| | (26.56) | (44.27) | (-8.23) | (46.57) | (61.08) | (-30.79) |

Table 4: **Structural Breaks in Stock Retail Ratios**

The first two columns present the intercepts and slope coefficients for the regression

$$Retail_{p,t} = \alpha_p + \beta_p I_t + \epsilon_{p,t} ,$$

where $Retail_{p,t}$ represents the average retail ratio of portfolio $p$ in month $t$. $I_t$ is a monthly dummy with value 1 after March 2020. The sample period ranges from January 2015 to December 2021. Newey-West standard errors with three lags are applied to calculate the $t$-statistics in parentheses. "Average H-L" is calculated as the equal-weighted average of the ten anomaly portfolio returns.

| | **Long-Short** | | **Long Leg** | | **Short Leg** | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| | $\alpha_p$ | $\beta_p$ | $\alpha_p$ | $\beta_p$ | $\alpha_p$ | $\beta_p$ |
| **Cross-Sectional Average** | | | 0.0664 | 0.0094 | | |
| | | | (93.69) | (7.70) | | |
| **Implied Volatility** | -0.0877 | -0.0266 | 0.0480 | -0.0008 | 0.1357 | 0.0257 |
| | (-38.64) | (-5.94) | (54.21) | (-0.48) | (66.26) | (6.79) |
| **Risk-neutral Variance** | -0.0725 | -0.0162 | 0.0515 | -0.0035 | 0.1240 | 0.0127 |
| | (-33.19) | (-4.59) | (49.97) | (-2.36) | (71.66) | (4.05) |
| **Risk-neutral Skewness** | -0.0929 | -0.0030 | 0.0412 | 0.0048 | 0.1341 | 0.0079 |
| | (-51.03) | (-0.79) | (70.65) | (3.47) | (71.18) | (1.95) |
| **Risk-neutral Kurtosis** | -0.0980 | -0.0151 | 0.0404 | 0.0027 | 0.1385 | 0.0178 |
| | (-50.33) | (-4.40) | (64.06) | (2.42) | (71.07) | (4.71) |
| **IV Term Spread** | -0.0013 | -0.0136 | 0.0871 | 0.0120 | 0.0884 | 0.0255 |
| | (-0.74) | (-2.17) | (63.39) | (3.65) | (53.77) | (5.78) |
| **Market Cap** | -0.0662 | -0.0147 | 0.0669 | 0.0051 | 0.1331 | 0.0198 |
| | (-33.54) | (-2.65) | (52.59) | (1.91) | (77.58) | (4.94) |
| **Option Bid-Ask Spread** | 0.0046 | 0.0397 | 0.0823 | 0.0305 | 0.0777 | -0.0092 |
| | (1.62) | (9.12) | (38.88) | (6.70) | (66.32) | (-5.73) |
| **Volatility Risk Premium** | -0.0013 | -0.0230 | 0.0957 | 0.0056 | 0.0971 | 0.0286 |
| | (-0.57) | (-1.88) | (50.40) | (0.70) | (59.22) | (5.44) |
| **Option Momentum** | 0.0048 | -0.0034 | 0.0879 | -0.0049 | 0.0832 | -0.0015 |
| | (2.68) | (-1.14) | (54.69) | (-2.01) | (74.66) | (-0.64) |
| **Idiosyncratic Volatility** | -0.0942 | -0.0162 | 0.0459 | -0.0008 | 0.1167 | 0.0224 |
| | (-44.52) | (-3.14) | (52.23) | (-0.49) | (75.09) | (5.84) |
| **Average H - L** | -0.0505 | -0.0092 | 0.0647 | 0.0051 | 0.1152 | 0.0143 |
| | (-39.56) | (-4.50) | (79.13) | (4.61) | (82.87) | (5.47) |

Table 5: **A Retail Factor**

Column (1) presents the average delta-hedged returns for calls sorted by stock retail ratios. Columns (2) and (3) display the intercept and slope coefficients of the regression

$$R_{p,t} = \alpha_p + \beta_p I_t + \epsilon_{p,t} \,,$$

where $R_{p,t}$ is the return on portfolio $p$ in month $t$ and $I_t$ is a monthly dummy with value 1 after March 2020. The sample period ranges from January 2015 to December 2021. Newey-West standard errors with three lags are used to calculate $t$-statistics.

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| | **Return** | $\alpha_p$ | $\beta_p$ |
| **Low** | -0.0026 | -0.0008 | -0.0068 |
| | (-3.20) | (-1.00) | (-4.03) |
| **2** | -0.0021 | -0.0006 | -0.0060 |
| | (-2.80) | (-0.72) | (-3.77) |
| **3** | -0.0022 | -0.0009 | -0.0053 |
| | (-3.13) | (-1.19) | (-3.37) |
| **4** | -0.0019 | -0.0006 | -0.0050 |
| | (-2.53) | (-0.76) | (-3.08) |
| **5** | -0.0015 | -0.0001 | -0.0059 |
| | (-2.02) | (-0.09) | (-3.56) |
| **6** | -0.0026 | -0.0011 | -0.0059 |
| | (-3.38) | (-1.32) | (-3.63) |
| **7** | -0.0027 | -0.0009 | -0.0074 |
| | (-3.32) | (-1.02) | (-4.26) |
| **8** | -0.0037 | -0.0019 | -0.0071 |
| | (-4.33) | (-2.09) | (-3.95) |
| **9** | -0.0047 | -0.0021 | -0.0102 |
| | (-4.90) | (-2.24) | (-5.31) |
| **High** | -0.0104 | -0.0059 | -0.0177 |
| | (-7.65) | (-4.82) | (-7.16) |
| **High - Low** | -0.0078 | -0.0051 | -0.0109 |
| | (-8.16) | (-5.44) | (-5.80) |

Table 6: **Magnitude of Structural Breaks with the Retail Factor as a Control**
The table reports parameter estimates from the regression

$$R_{p,t} = \alpha_p + \beta_p I_t + \gamma_p f_{retail,t} + \epsilon_{p,t} \,,$$

where $R_{p,t}$ is the return for portfolio $p$ at month $t$, $I_t$ is a monthly dummy with value 1 after March 2020, and $f_{retail,t}$ is the retail factor. "Average H-L" is calculated as the equal-weighted average of the ten anomaly portfolio returns. The sample period ranges from January 2015 to December 2021. Newey-West standard errors with three lags are used to calculate the $t$-statistics in parentheses.

| | **Long-Short** | | |
|---|---|---|---|
| | $\alpha_p$ | $\beta_p$ | $\gamma_p$ |
| **Implied Volatility** | 0.0067 | 0.0099 | 0.7363 |
| | (6.49) | (5.51) | (10.28) |
| **Risk-Neutral Variance** | 0.0062 | 0.0043 | 0.7214 |
| | (6.38) | (2.56) | (8.83) |
| **Risk-Neutral Skewness** | 0.0027 | 0.0045 | 0.6192 |
| | (3.78) | (2.70) | (8.50) |
| **Risk-Neutral Kurtosis** | 0.0038 | 0.0056 | 0.7221 |
| | (5.88) | (3.23) | (10.90) |
| **IV Term Spread** | 0.0052 | 0.0029 | -0.1609 |
| | (3.84) | (1.79) | (-1.12) |
| **Market Cap** | 0.0021 | 0.0070 | 0.7922 |
| | (2.51) | (4.02) | (8.65) |
| **Option Bid-Ask Spread** | 0.0032 | 0.0026 | 0.3433 |
| | (3.54) | (2.14) | (3.74) |
| **Volatility Risk-Premium** | 0.0079 | 0.0098 | -0.1727 |
| | (4.11) | (3.62) | (-0.72) |
| **Option Momentum** | 0.0065 | 0.0060 | -0.0066 |
| | (7.15) | (4.06) | (-0.08) |
| **Idiosyncratic Volatility** | 0.0019 | -0.0001 | 1.1023 |
| | (2.21) | (-0.05) | (10.05) |
| **Average H-L** | 0.0046 | 0.0052 | 0.4697 |
| | (8.40) | (5.53) | (9.96) |

Table 7: **Retail Ratios and Lottery Features**
This table presents the coefficients and $t$-statistics from Fama-Macbeth regressions where the stock or option retail ratio is the dependent variable. The independent variables include five lottery characteristics (log(Stock Price), Idiosyncratic Volatility, Max Return, Jackpot, Expected Idiosyncratic Skew), a proxy for past stock price trends, and an attention measure constructed from Google search volume. All variables are standardized. Panel A displays the results of univariate regression using lottery features, past trend, and attention, as well as multiple regressions incorporating trend and attention measures and one lottery proxy, with the stock retail ratio as the dependent variable. Panel B presents the results in which the option retail ratio is the dependent variable. Results for the stock retail ratio uses the sample from January 2015 to December 2021, while results for option retail ratios use November 2019 to December 2021. We use Newey-West standard errors with three lags.

**Panel A: Stock retail ratios**

| | **Univariate Regressions** | | **Multiple Regressions** | | | |
|---|---|---|---|---|---|---|
| | **Coeff** | **Adj R2** | **Lottery** | **Past Trend** | **Attention** | **Adj R2** |
| **Expected Idiosyncratic Skew** | 0.4360 | 0.2211 | 0.4476 | 0.0838 | 0.0838 | 0.2501 |
| | (22.71) | | (23.98) | (7.43) | (12.53) | |
| **Jackpot** | 0.4202 | 0.1991 | 0.4281 | 0.0639 | 0.0905 | 0.2178 |
| | (41.52) | | (35.76) | (5.72) | (14.10) | |
| **Max Return** | 0.3800 | 0.1492 | 0.3869 | 0.0663 | 0.0576 | 0.1760 |
| | (44.74) | | (43.90) | (6.90) | (7.84) | |
| **log(Stock Price)** | -0.4243 | 0.1829 | -0.4186 | 0.0770 | 0.0707 | 0.2042 |
| | (-34.72) | | (-33.66) | (7.56) | (8.23) | |
| **Idiosyncratic Volatility** | 0.5653 | 0.3283 | 0.5667 | 0.0049 | 0.0737 | 0.3437 |
| | (59.66) | | (59.16) | (0.51) | (11.62) | |
| **Past Trend** | 0.0601 | 0.0244 | | | | |
| | (4.28) | | | | | |
| **Attention** | 0.0491 | 0.0032 | | | | |
| | (5.75) | | | | | |

**Panel B: Option retail ratios**

| Univariate Regressions | | | Multiple Regressions | | | |
|---|---|---|---|---|---|---|
| | **Coeff** | **Adj R2** | **Lottery** | **Past Trend** | **Attention** | **Adj R2** |
| **Expected Idiosyncratic Skew** | 0.2751 | 0.0825 | 0.2795 | 0.0265 | -0.0014 | 0.0868 |
| | (7.53) | | (7.56) | (1.49) | (-0.20) | |
| **Jackpot** | 0.2782 | 0.0829 | 0.2859 | -0.0029 | 0.0169 | 0.0872 |
| | (11.79) | | (12.17) | (-0.24) | (2.98) | |
| **Max Return** | 0.1260 | 0.0185 | 0.1199 | 0.0007 | 0.0107 | 0.0211 |
| | (7.36) | | (7.70) | (0.06) | (1.50) | |
| **log(Stock Price)** | -0.4326 | 0.1958 | -0.4353 | 0.0069 | 0.0282 | 0.1995 |
| | (-12.57) | | (-12.63) | (0.87) | (5.43) | |
| **Idiosyncratic Volatility** | 0.2539 | 0.0713 | 0.2537 | -0.0305 | 0.0136 | 0.0724 |
| | (7.83) | | (8.40) | (-2.63) | (1.75) | |
| **Past Trend** | 0.0054 | 0.0053 | | | | |
| | (0.37) | | | | | |
| **Attention** | 0.0097 | -0.0002 | | | | |
| | (1.33) | | | | | |

Table 8: **Average Lottery Characteristics for Option Portfolios**

Using decile sorts on various option anomaly characteristics, we compute average lottery characteristics for the stocks whose options are held in the long and short legs of the anomaly portfolio. The table reports the time series means of these ratios, as well as the differences between them (computed as short minus long), with $t$-statistics in parentheses. All averages are computed for the period from January 2015 to December 2021. Newey-West standard errors use three lags.

| | **E[Idiosyncratic Skew]** | | | **Jackpot** | | | **Max Return** | | | **log(Stock Price)** | | | **Idiosyncratic Volatility** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Long** | **Short** | **S-L** | **Long** | **Short** | **S-L** | **Long** | **Short** | **S-L** | **Long** | **Short** | **S-L** | **Long** | **Short** | **S-L** |
| **Implied Volatility** | 0.00 | 1.68 | 1.67 | 0.02 | 0.07 | 0.05 | 0.03 | 0.13 | 0.09 | 4.50 | 2.19 | -2.31 | 0.01 | 0.05 | 0.04 |
| | (0.06) | (12.07) | (12.46) | (44.63) | (23.86) | (19.77) | (13.76) | (19.00) | (18.96) | (166.89) | (97.10) | (-56.67) | (20.07) | (21.72) | (21.31) |
| **Risk-neutral Variance** | 0.01 | 1.52 | 1.52 | 0.02 | 0.07 | 0.05 | 0.03 | 0.12 | 0.08 | 4.65 | 2.37 | -2.29 | 0.01 | 0.05 | 0.04 |
| | (0.20) | (13.10) | (13.41) | (45.45) | (27.76) | (23.59) | (14.13) | (22.68) | (24.47) | (103.83) | (97.22) | (-36.06) | (21.05) | (24.99) | (25.17) |
| **Risk-neutral Skewness** | 0.27 | 1.49 | 1.22 | 0.03 | 0.07 | 0.04 | 0.05 | 0.10 | 0.06 | 3.81 | 1.89 | -1.92 | 0.02 | 0.04 | 0.03 |
| | (5.36) | (12.53) | (12.72) | (38.98) | (29.81) | (22.39) | (16.26) | (25.03) | (28.06) | (124.93) | (85.46) | (-50.45) | (20.06) | (28.67) | (30.72) |
| **Risk-neutral Kurtosis** | 0.21 | 1.60 | 1.38 | 0.03 | 0.07 | 0.04 | 0.04 | 0.11 | 0.07 | 3.94 | 1.90 | -2.04 | 0.02 | 0.05 | 0.03 |
| | (4.71) | (11.69) | (11.59) | (43.58) | (26.37) | (19.20) | (17.65) | (19.62) | (18.26) | (182.16) | (111.39) | (-81.95) | (20.78) | (22.35) | (21.51) |
| **IV Term Spread** | 0.93 | 1.02 | 0.09 | 0.04 | 0.05 | 0.00 | 0.08 | 0.09 | 0.02 | 3.04 | 2.87 | -0.17 | 0.03 | 0.04 | 0.00 |
| | (9.78) | (10.55) | (3.09) | (33.94) | (24.81) | (4.06) | (21.08) | (16.43) | (4.66) | (65.30) | (79.79) | (-5.52) | (24.92) | (22.33) | (4.28) |
| **Market Cap** | 0.05 | 1.63 | 1.59 | 0.01 | 0.07 | 0.06 | 0.04 | 0.10 | 0.06 | 4.79 | 1.96 | -2.83 | 0.01 | 0.04 | 0.03 |
| | (1.25) | (12.16) | (11.83) | (37.07) | (28.56) | (24.52) | (13.32) | (21.57) | (26.56) | (90.30) | (71.37) | (-36.88) | (20.26) | (25.38) | (27.59) |
| **Option Bid-Ask Spread** | 0.27 | 0.88 | 0.61 | 0.02 | 0.05 | 0.02 | 0.06 | 0.07 | 0.01 | 4.20 | 2.89 | -1.30 | 0.02 | 0.03 | 0.01 |
| | (5.63) | (11.51) | (12.14) | (34.29) | (32.62) | (24.37) | (12.54) | (23.79) | (4.67) | (132.46) | (130.83) | (-32.53) | (14.04) | (35.28) | (8.52) |
| **Volatility Risk Premium** | 1.04 | 1.19 | 0.16 | 0.05 | 0.05 | 0.00 | 0.10 | 0.09 | -0.01 | 3.14 | 2.52 | -0.62 | 0.05 | 0.03 | -0.01 |
| | (10.12) | (11.23) | (2.69) | (27.11) | (30.13) | (1.12) | (29.85) | (16.24) | (-3.33) | (88.36) | (60.15) | (-10.48) | (20.80) | (24.38) | (-9.75) |
| **Option Momentum** | 0.76 | 1.14 | 0.38 | 0.04 | 0.05 | 0.00 | 0.09 | 0.07 | -0.02 | 3.44 | 2.75 | -0.69 | 0.04 | 0.03 | 0.00 |
| | (11.03) | (12.94) | (6.12) | (19.26) | (45.39) | (0.88) | (22.67) | (28.70) | (-8.91) | (49.30) | (103.35) | (-10.18) | (40.73) | (32.06) | (-8.14) |

Table 9: **Magnitudes of Structural Breaks with the Lottery Factor as a Control**
The table reports the coefficient estimates for the regression

$$R_{p,t} = \alpha_p + \beta_p I_t + \gamma_p f_{lottery,t} + \epsilon_{p,t} \ ,$$

where $R_{p,t}$ is the return for portfolio $p$ at month $t$, $I_t$ is a monthly dummy with value 1 after March 2020, and $f_{lottery,t}$ is the lottery factor. In addition to the ten anomaly portfolios, the table includes the equally-weighted average anomaly portfolio and the long-short retail factor. The sample period is from January 2015 to December 2021. Newey-West standard errors with three lags are used to calculate the $t$-statistics in parentheses.

| | **Long-Short** | | |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| | $\alpha_p$ | $\beta_p$ | $\gamma_p$ |
| **Implied Volatility** | 0.0043 | 0.0055 | 0.4221 |
| | (4.06) | (2.42) | (8.11) |
| **Risk-neutral Variance** | 0.0040 | 0.0003 | 0.4057 |
| | (3.85) | (0.18) | (9.87) |
| **Risk-neutral Skewness** | 0.0011 | 0.0018 | 0.3247 |
| | (1.43) | (0.94) | (7.12) |
| **Risk-neutral Kurtosis** | 0.0022 | 0.0029 | 0.3603 |
| | (2.42) | (1.23) | (7.15) |
| **IV Term Spread** | 0.0049 | 0.0023 | -0.0379 |
| | (3.12) | (1.32) | (-0.61) |
| **Market Cap** | -0.0003 | 0.0026 | 0.4435 |
| | (-0.58) | (2.60) | (21.82) |
| **Option Bid-Ask Spread** | 0.0020 | 0.0004 | 0.2022 |
| | (2.34) | (0.36) | (6.03) |
| **Volatility Risk Premium** | 0.0078 | 0.0094 | -0.0510 |
| | (3.64) | (3.13) | (-0.53) |
| **Option Momentum** | 0.0062 | 0.0053 | 0.0206 |
| | (4.68) | (2.86) | (0.33) |
| **Idiosyncratic Volatility** | -0.0002 | -0.0035 | 0.5261 |
| | (-0.24) | (-2.95) | (21.44) |
| **Average LS** | 0.0032 | 0.0027 | 0.2616 |
| | (6.23) | (2.85) | (15.53) |
| **Retail Factor** | -0.0001 | 0.0004 | 0.3578 |
| | (-0.14) | (0.34) | (10.30) |

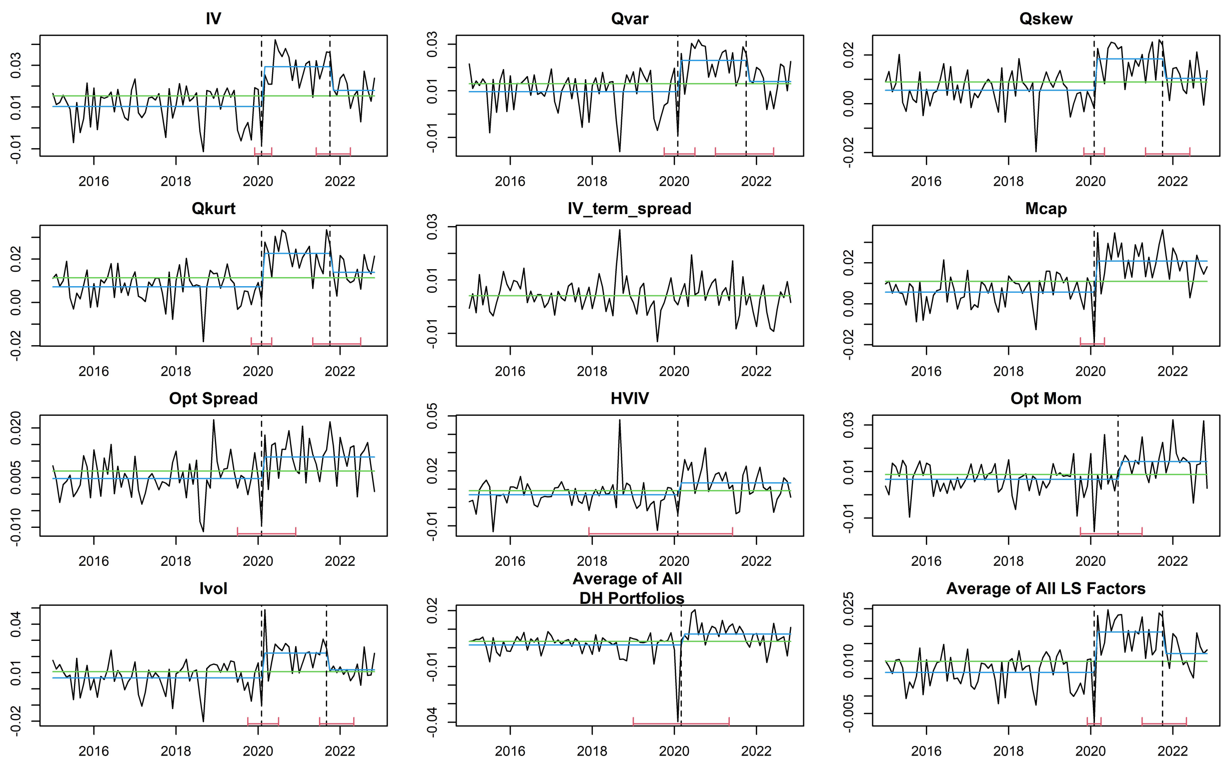


Figure 1: Structural Changes in Anomaly Returns

The plots show the time-series of monthly returns for the long-short portfolios formed on implied volatility (IV), risk-neutral variance (Qvar), risk-neutral skewness (Qskew), risk-neutral kurtosis (Qkurt), the implied volatility term spread (IV term spread), market capitalization (Mcap), option bid-ask-spread (Opt Spread), the difference between 365-day historical volatility and the one-month implied volatility (HVIV), 12-month option momentum (Opt Mom), and idiosyncratic volatility (Ivol). It also includes an equally-weighted average of all delta-hedged portfolios, and an average of all ten long-short anomaly portfolios. Dashed lines denote the breakpoints identified by the Bai & Perron (1998) test, and red lines indicate the 95% confidence intervals for these breakpoints. Blue lines depict the average returns for the periods in between breakpoints, whereas green lines represent the average return for the entire sample. The sample period is from January 1996 to December 2022.

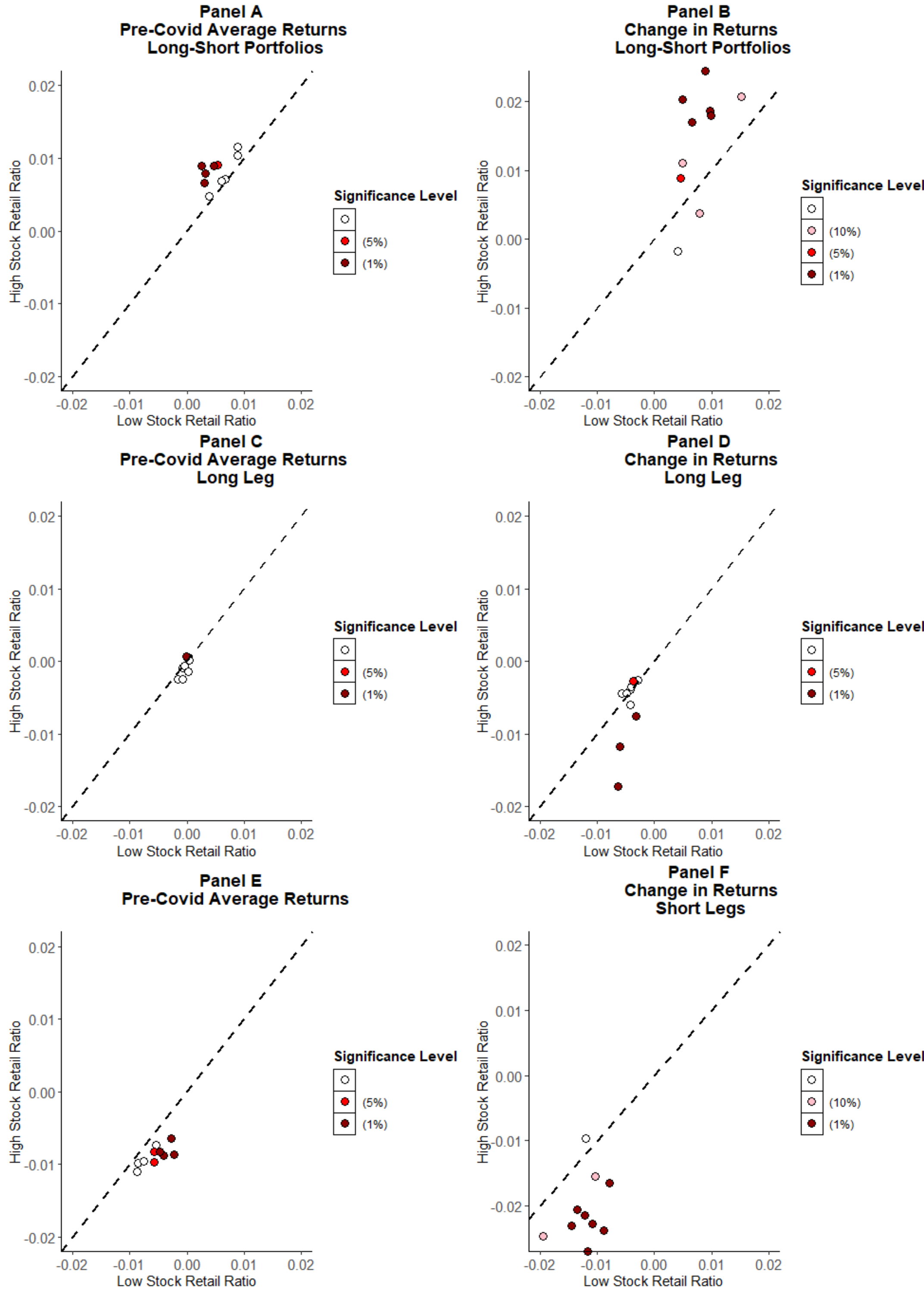


Figure 2: Anomaly Returns and Structural Break Sizes: High vs. Low Stock Retail Ratios

Panel A shows the average returns for each anomaly portfolio over the period from January 2015 to March 2020. The x-axis (y-axis) represents returns on anomaly portfolios constructed from options with low (high) stock retail ratios. Panel B shows the corresponding changes in anomaly returns after March 2020. Panels C through F are analogous but show only the returns on the anomalies' long or short legs. Colors denote the significance of the differences in returns (or changes in returns) between the portfolios constructed from high and low retail ratios. The full sample period is from January 2015 to December 2021.

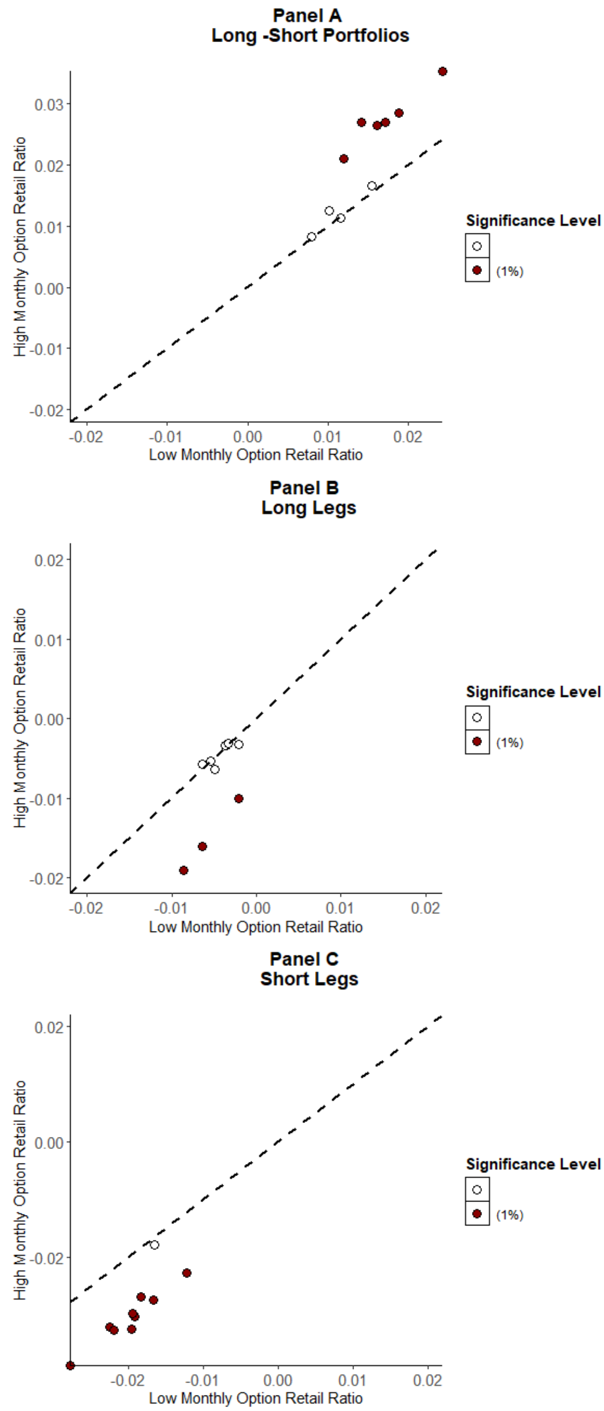


Figure 3: Anomaly Returns after March 2020: High vs. Low Option Retail Ratios

Panel A shows the average returns for each anomaly portfolio over the period from April 2020 to December 2021. The x-axis (y-axis) represents returns on anomaly portfolios constructed from options with low (high) option retail ratios. Panels B and C are analogous but show only the returns on the anomalies' long or short legs. Colors denote the significance of the differences in returns (or changes in returns) between the portfolios constructed from high and low retail ratios.

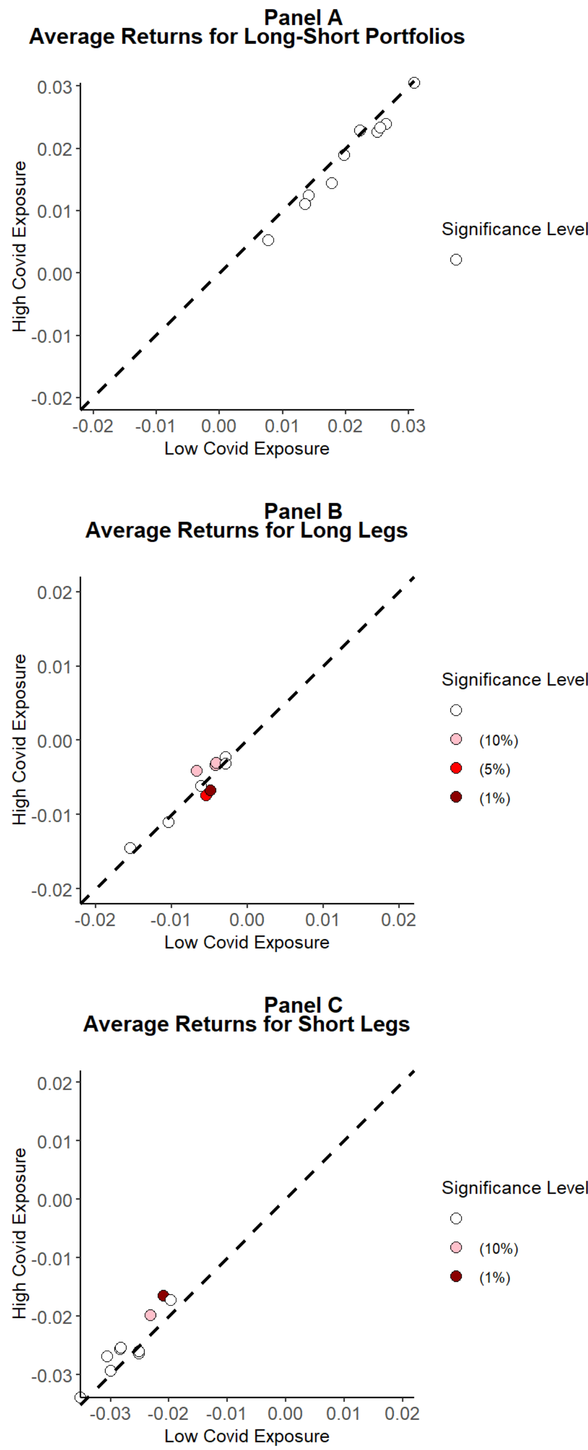


Figure 4: Anomaly Returns after Structure Break: Comparing High vs. Low Covid Exposure

Panel A shows the average returns for each anomaly portfolio over the period from April 2020 to December 2021. The x-axis (y-axis) represents returns on anomaly portfolios constructed from options with low (high) Covid exposure. Panels B and C are analogous but show only the returns on the anomalies' long or short legs. Colors denote the significance of the differences in returns (or changes in returns) between the portfolios constructed from high and low Covid exposures.

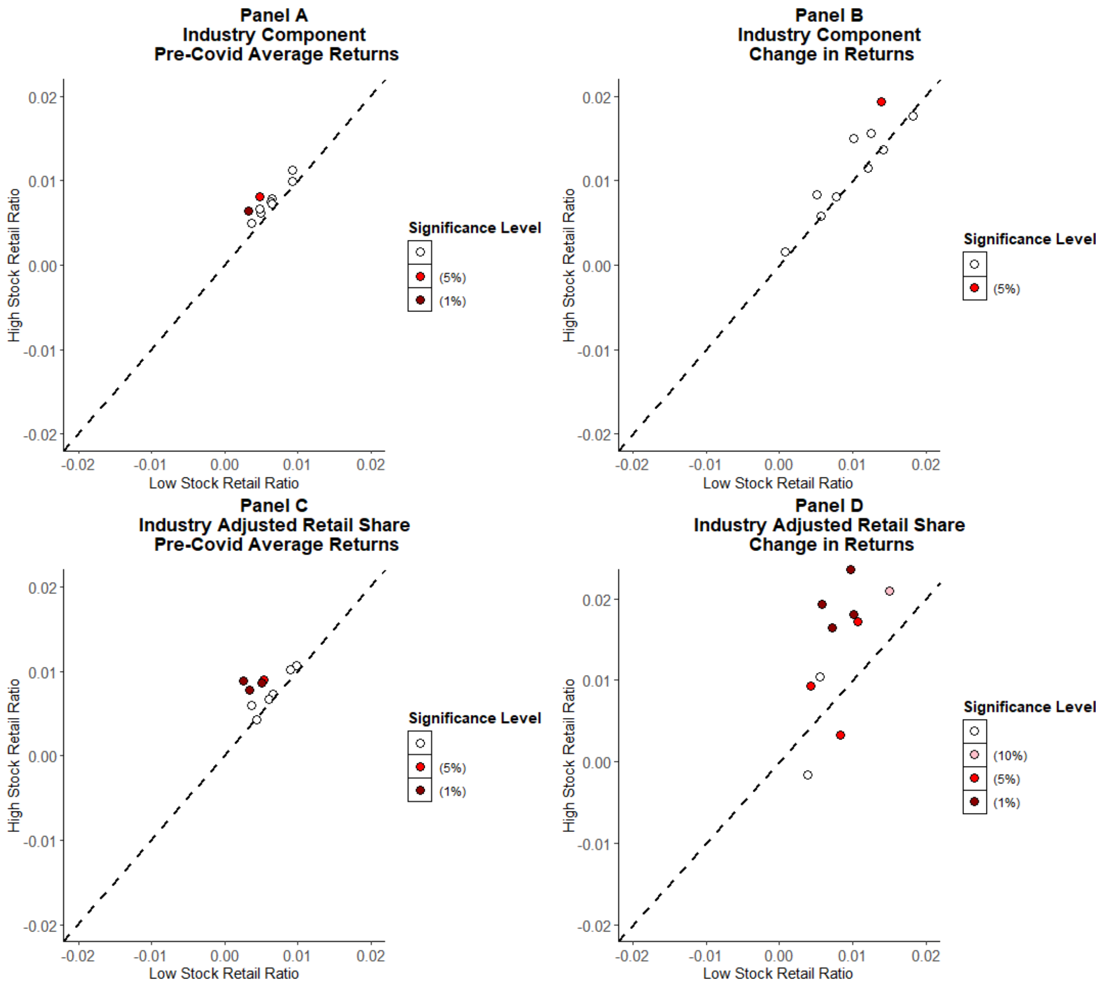


Figure 5: Anomaly Returns and Structural Break Sizes: Industries and Industry-Adjustment

Panel A shows the average returns for each anomaly portfolio over the period from January 2015 to March 2020. The x-axis (y-axis) represents returns on anomaly portfolios constructed from options in industries with low (high) stock retail ratios. Panel B shows the corresponding changes in anomaly returns after March 2020. Panels C and D are analogous but instead segment firms based on industry-adjusted stock retail ratios. We use 17 industries from the French Data Library. Colors denote the significance of the differences in returns (or changes in returns) between the portfolios constructed from high and low industry or industry-adjusted retail ratios. The full sample period is from January 2015 to December 2021.

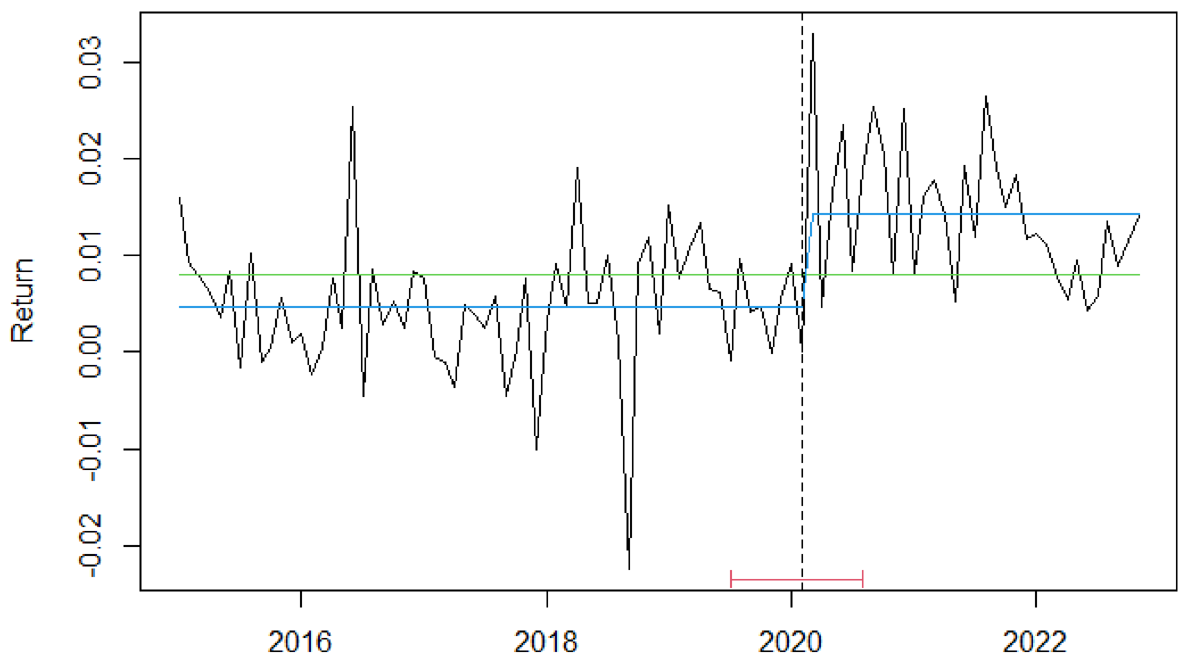


Figure 6: The Retail Factor

The figures show the time-series of monthly returns for the retail factor, which goes long the decile of stocks with the lowest stock retail ratio and shorts the decile with the highest stock retail ratio. The dashed line denotes the breakpoint identified by the Bai & Perron (1998) test, and red lines indicate the 95% confidence interval for that breakpoint. Blue lines depict the average returns for the periods in between breakpoints, whereas the green line represents the average return for the entire sample. The sample period is from January 1996 to December 2022.

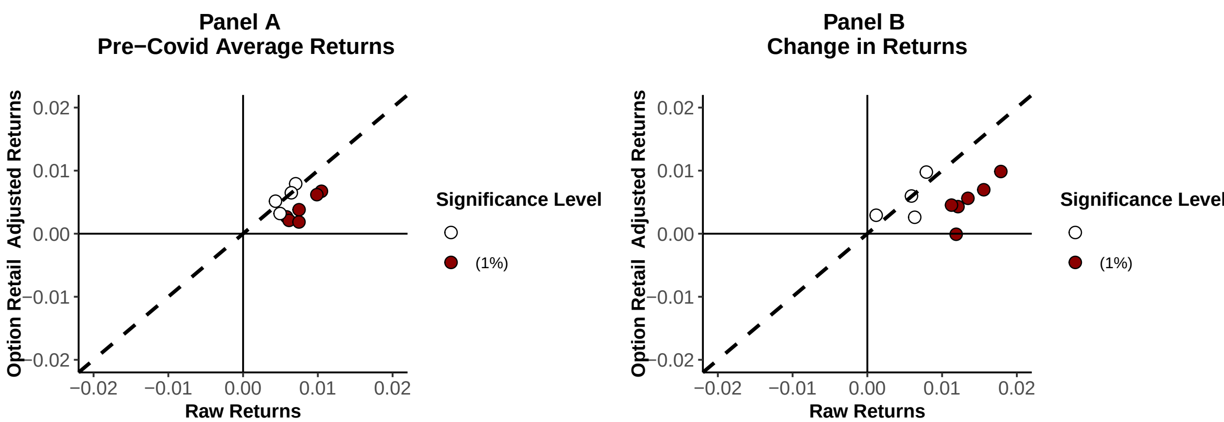


Figure 7: Raw vs. Retail-Adjusted Anomaly Returns

Panel A shows the average anomaly returns for from January 2015 to March 2020. The x-axis shows the raw return, while the y-axis shows the abnormal return after controlling for the retail factor. Panel B shows the corresponding changes in anomaly returns after March 2020. Colors denote the significance of the differences between raw and adjusted returns (or changes in returns). The full sample period is from January 2015 to December 2021.

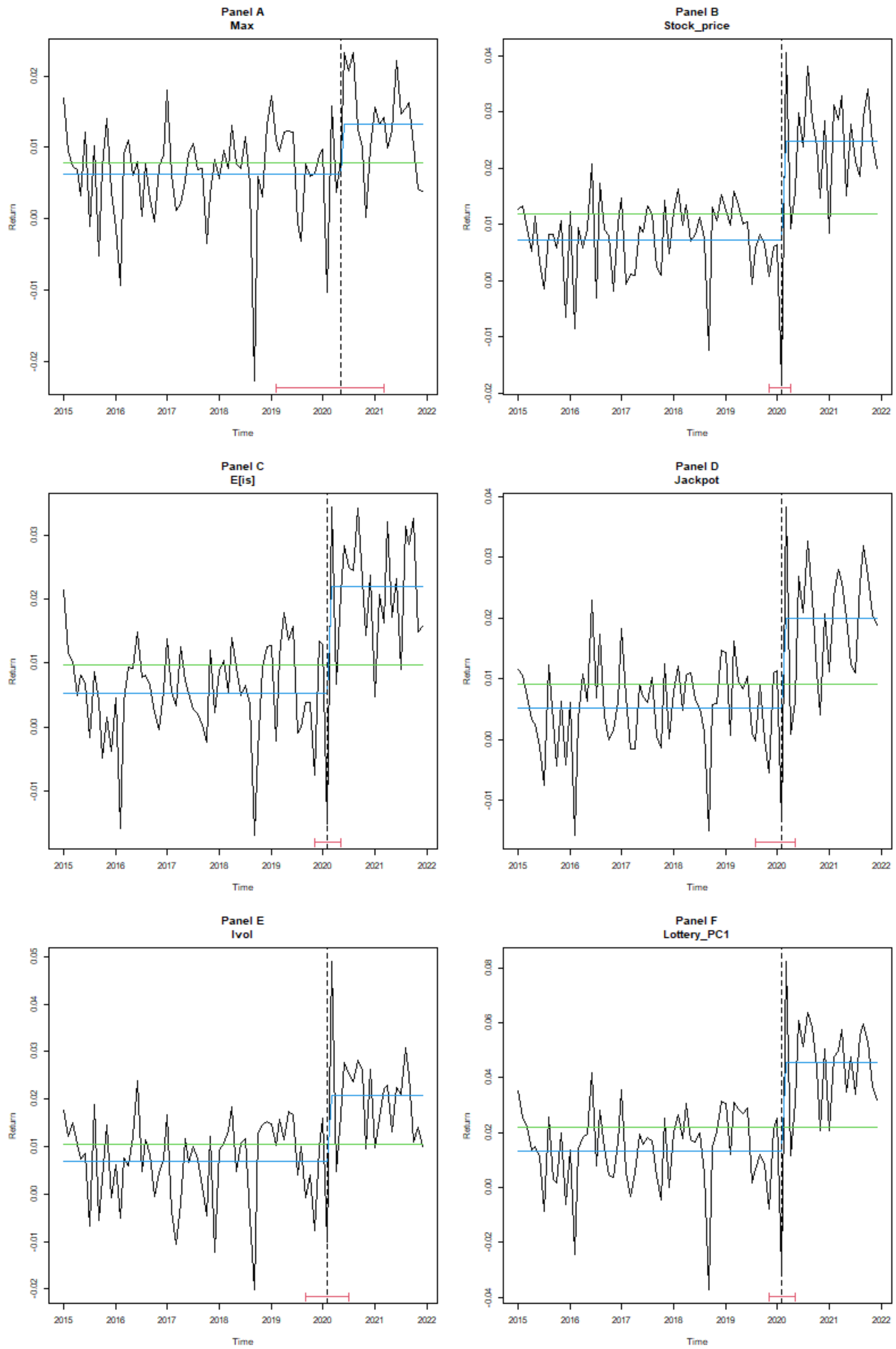


Figure 8: Structural Breaks in Lottery-Like Factors

The plots show the time-series of monthly returns for six different lottery-like factors. The first five are from decile sorts on maximum daily stock return, stock price, expected idiosyncratic skewness, Jackpot probability, and idiosyncratic volatility. The last shows a lottery factor equal to the first principal component of the first five. Dashed lines denote the breakpoints identified by the Bai & Perron (1998) test, and red lines indicate the 95% confidence intervals for these breakpoints. Blue lines depict the average returns for the periods in between breakpoints, whereas green lines represent the average return for the entire sample. The sample period is from January 1996 to December 2021.