Peer Option Momentum*

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Abstract

We find strong evidence of peer momentum in delta-hedged option returns. Our main peer momentum measure, in which firms are linked if they share common sell-side analysts, is highly profitable, with a pre-cost Sharpe ratio of 3. It is distinct from standard momentum, and there is little impact from controlling for standard momentum or other well-know option return predictors. It is robust to the length of the formation periods, the method of return computation, and realistic assumptions about transactions costs. Alternative methods for linking peer firms usually result in weaker performance, though it in most cases remains highly significant. We show that peer momentum is consistent with underreaction of implied volatilities to volatility shocks of peer firms. Using several different approaches, we also show that factor momentum only partially explains peer momentum, and vice versa. Our final results demonstrate the new finding of peer reversal, which is present in a smaller number of firm pairs but is nevertheless highly significant.

Keywords: options, peer momentum

*All errors are our own. Comments welcome!

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1 Introduction

It is likely that, on any given day, most value-relevant information about a firm comes from announcements and news articles written primarily or entirely about other firms. A firm only has four earnings announcements per year, for example, but its competitors may have hundreds. As such, price discovery is largely the process of learning about how the value of a particular firm should be updated based on news about other firms. These firms may be similar in some characteristic, possess shared owners or analysts, or be related as customers or suppliers.

A large literature that focuses on the equity market has explored the nature of this process, finding numerous examples of anomalous responses to news from related firms. Moskowitz and Grinblatt (1999), for example, demonstrated lead-lag relations among firms in the same industry, while Menzly and Ozbas (2010) find similar patterns in the returns of customer firms and their suppliers. Ali and Hirshleifer (2020) find that sharing common sell-side analysts subsumes other types of connection. Because this work universally finds positive lead-lag relations between the returns of related firms, the phenomenon can be viewed as a generalization of the momentum phenomenon discovered by Jegadeesh and Titman (1993) and is often referred to as "peer momentum."

In the equity market, momentum is a robust and well-explored subject. Only recently, however, Heston et al. (2023) demonstrated that momentum is an even stronger empirical regularity in the options market. They concluded that the strategy most likely reflects the option market's underreaction to the stock's past volatility surprises. But if options on a stock underreact to that firm's own shocks, then it seems reasonable to expect that they will also underreact to the volatility shocks of other firms. This would result in *peer option momentum*, which is the phenomenon we study in this paper.

As is common in the empirical options literature, we study returns-to-expiration on zero-delta straddles. This choice imposes less stringent data requirements, needing only the observation of a single put-call pair on the portfolio formation date. One benefit is to maximize the number of pairings between each firm and its peers, which are those firms that share at least one common analyst (following Ali and Hirshleifer 2020). We rebalance the stock hedge daily to maintain a zero delta, enduring that our findings are not mechanically driven by peer momentum in equities.

We examine peer momentum strategies formed over various formation periods, ranging from one month to five years, and find all to be significantly profitable. Our benchmark strategy, which uses a 12-month formation period, has an average return of more than 5% per month (ignoring transactions costs), with a corresponding t-statistic above 14. Its annualized Sharpe ratio is around 3. Moreover, the strategy has positive skewness and unexceptional tail behavior.

Peer momentum is distinct from regular momentum, retaining high levels of statistical significance in double sorts or in Fama-MacBeth regressions that control for momentum. We also find little effect after controlling for other powerful option return predictors, such as the difference between historical and implied volatility (Goyal and Saretto 2009), the implied volatility term spread (Vasquez 2017), or idiosyncratic stock volatility (Cao and Han 2013).

We find that peer momentum is stronger for a given "focal" firm when it is smaller, has less analyst coverage, has a higher volume of options trading, or has less attention, as measured using Google search volume (Da et al. 2011) and EDGAR view (Lee et al. 2015). We also find some evidence that the effect is stronger when peer firms attract less attention, as measured by Google search volume and EDGAR view, though less direct measures of investor attention deliver consistent but not always significant results.

Our results are robust in a variety of ways. Besides formation period length, we consider alternative hedging strategies, including the bias-adjusted approach of Eberbach et al. (2025). We examine the effects of transactions costs following Muravyev and Pearson (2020). Overall, modest methodological choices have little effect on our results, which also survive reasonable transactions cost estimates.

We also consider ten other measures of firm connectedness besides shared analyst coverage. Most of these other measures of connectedness also result in significant peer momentum effects, and many of these retain significance after controlling for analyst-based peer momentum. But in all cases but one, analyst-based peer momentum remains highly significant after controlling for peer momentum based on other connections, including a composite connectedness measure that aggregates the effects of all connections, including shared analysts. Relative to Ali and Hirshleifer's (2020) study of peer momentum in the equity market, we find analyst connections to be the most important link between firms but not a unifying measure of connection. This may be natural given the sell-side analyst's primary role in researching equities rather than their options.

We examine the responses of realized and implied variances to peer momentum. Even after controlling for implied variance and "own" momentum, peer momentum has significant explanatory power for future realized variance. Peer momentum also impacts implied variances, but to a lesser degree. This muted reaction to peer information, which results in peer option momentum, could be the result of a behavioral bias. It could also be the result of time-varying risk premia.

We therefore consider next whether peer effects can be explained by factor risk premia, specifically in the form of factor momentum. In the equity market, both Ehsani and Linnainmaa (2021) and Gupta and Kelly (2019) find that momentum is primarily or even entirely explained by factor momentum. Recent papers by Käfer et al. (2025) and Beckmeyer et al. (2023) argue that this is also true for the options market. This is important given the similar though not identical predictions of peer and factor momentum, as discussed by Yan and Yu (2023).

We address this issue in several ways. First, following Beckmeyer et al. (2023), we directly measure the contributions of systematic-based and residual-based momentum in a flexible linear factor model. Analysis of this model, which is based on the instrumented principal components approach of Kelly et al. (2019), shows that systematic and residual momentum are approximately of equal importance. A shortcoming of this approach is that, while the model is very general, it is impossible to rule out that an alternative specification wouldn't deliver different results.

We also consider the option factor momentum strategy of Käfer et al. (2025), who argue that factor momentum subsumes own momentum. In contrast to their results, which are based on delta-hedged calls, our straddle-based results imply that factor and own momentum are only partially related. More importantly for our purposes, the factor momentum strategy of Käfer et al. (2025) only partially explains peer momentum returns, and vice versa.

Our last approach therefore builds on the model-free methods of Kelly et al. (2023) and Yan and Yu (2023), in which we look for violations of the symmetric nature of factor momentum. In essence, factor momentum predicts that if firm A's returns positively predict firm B's returns, then the reverse relation should be equally strong. In contrast, it is possible though not guaranteed that peer momentum might be asymmetric; firm A could predict firm B without the reverse relation being as strong or even present at all. We examine analyst-based peers for evidence of such imbalanced responses.

We find that analyst-based connections are mostly symmetric, which could but does not necessarily arise from factor momentum. However, there is also a smaller but highly significant asymmetric component that cannot be explained by factor momentum, indicating that true peer momentum is present.

Finally, we examine a data-driven peer momentum strategy, which does not rely on analyst links. The returns on this version of peer momentum are competitive with the analyst-based strategy, but neither spans the other in the sense of Barillas and Shanken (2018). Each represents a sizeable, significant, and distinct source of expected returns.

Perhaps more interestingly, this analysis reveals the presence of peer *reversal* in a minority of firm pairings. The prevalence of peer reversal is surprising because, to the best of our knowledge, the asset pricing literature has generally documented peer momentum in cross-firm lead-lag relations.

We begin in the next section by describing our data. Section 3 presents our main results, while Section 4 tackles the problem of distinguishing peer and factor momentum. Section 5 explores data-driven strategies and peer reversal. Section 6 concludes.

2 Data

2.1 Data sources and filters

We obtain option prices from the OptionMetrics Ivy DB database, which provides daily closing bid and ask quotes for the U.S. equity options. We use the Institutional Brokers Estimate System (IBES) database to obtain information on analyst coverage. Information about stock prices is extracted from CRSP.

In the construction of alternative firm linkages, we use the Text-based Network Industry Classifications from Gerard Hoberg's website (Hoberg and Phillips 2016), firms' headquarter location from Compustat (Parsons et al. 2020), firms' principal customers information from the supply chain data in WRDS linking queries (Cohen and Frazzini 2008), supplier and customer industry information from the input-output account data of Bureau of Economic Analysis (Menzly and Ozbas 2010), firms' business segment information from the Compustat segment file in WRDS (Cohen and Lou 2012), firms' patent information from Leonid Kogan's website (Lee et al. 2019), and the 209 firm charateristics data from the open source asset pricing website (Chen and Zimmermann 2022).

2.2 Straddle returns

Most of our analysis focuses on at-the-money (ATM) straddles on common equities over the period from January 1996 to November 2024. These straddles consist of one put and one call with the same strike price, which is closest to the current underlying stock price. We form each straddle on the third Friday of the month[1] and hold it until expiration, which is typically the third Friday of the following month. Thus, straddle returns are measured at the monthly frequency. To maintain delta neutrality throughout the holding period, we hedge the straddle by taking a position in the underlying stock. We use deltas given by OptionMetrics and rebalance the delta hedge daily until expiration.[2] Gains and losses from the delta hedge are reinvested at the risk-free rate. While all returns in this paper are excess returns, we refer to them as "returns" for brevity.

To summarize, the straddle return is measured as following:

$$\frac{Straddle(T) - \sum_{n=0}^{N-1} \triangle_{t_n}[S_{t_{n+1}} - S_{t_n} e^{r_f(t_{n+1}-t_n)}]e^{r_f(T-t_{n+1})}}{Straddle(t)} - R_{f,t\to T} \tag{1}$$

Here, $Straddle(T)$ is the final payoff of straddle at expiration T; $Straddle(t)$ is the initial value of straddle at formation day t; Delta-hedged positions are rebalanced at each of the business days $t_n, n = 0, 1, ..., N-1$, with $t_0 = t, t_N = T$; $\triangle_{t_n}$ is the delta of the straddle at day t_n; S_{t_n} is the stock price at day t_n; r_f is the daily log risk-free rate;[3] $R_{f,t\to T}$ is the monthly return on the risk-free asset.

To ensure the tradability of straddles, we apply a number of filters. First, we remove options with zero open interest or bid price. Second, we delete options whose ask prices are

[1]If the 3rd Friday of the month is a holiday, we use the Thursday immediately preceding it.

[2]In some cases, the Black-Scholes delta for an option is missing in the Optionmetrics. When this occurs, we estimate a delta using the stock price on that day and the most recent non-missing implied volatility for the same option.

[3]To calculate r_f, we interpolate the curve of the zero-coupon interest rates provided by the OptionMetrics on date t to match the option maturity and assume that r_f stays constant during the option holding period.

lower than bid prices, and those with prices violating arbitrage bounds. Third, we discard options with missing implied volatilities or deltas. We apply these filters only at the start of the holding period, thereby avoiding the look-ahead biases discussed by Duarte et al. (2025). We also exclude options whose underlying stock prices are lower than $5 at the formation day, as well as those with stock-splits during the holding period. Option contracts passing the above filters tend to be actively traded and have reliable returns.

Naturally, these filters reduce the sample size, particularly the requirement of positive open interest. Following Heston et al. (2023) and Heston et al. (2025), we compute a separate set of straddle returns after omitting the first filter. This set is only used to construct the momentum and peer momentum signals during the portfolio formation period. While it is possible that including these less liquid options introduces noise or bias, this should only lower the efficacy of our signal and bias against finding predictability using these signals.

2.3 The main peer momentum signal

We follow Ali and Hirshleifer (2020) and consider a stock to be covered by an analyst if that analyst issued at least one FY1 or FY2 earnings forecast for the stock during the 12 months leading up to a portfolio formation date. Two stocks are said to be connected if they are simultaneously covered by the same analyst. For a given "focal" stock, we use the term "peers" to denote all the stocks that are connected to it via shared analyst coverage.

After identifying the peers for each firm, we construct the peer momentum (PM) signal for each firm i using its peers' historical straddle returns. We consider different formation periods, but we focus more on the PM signals based on the most recent month or year. To compute the PM signal, we first compute the simple average straddle return, or momentum, of each peer firm during the formation period. Following Heston et al. (2025), we require each peer firm to have non-missing returns in at least two thirds of the months in the formation period. We then calculate firm i's PM signal by taking the average momentum across all its peers, where we weight by the number of shared analysts:

$$PM_i = \frac{1}{\sum_{j=1}^{N} n_{ij}} \sum_{j=1}^{N} n_{ij} MOM_j.$$

Here, n_{ij} is the number of analysts who cover both stocks i and j, N is the total number of firm i's peer firms, and MOM_j is the average option return of firm j over the formation period. This weighting scheme follows Ali and Hirshleifer (2020) and has the intuition that peers with more shared analysts are likely to have stronger fundamental linkages with the firm, and should therefore receive larger weights.

2.4 Alternative peer connection measures

If volatility information spillovers across peers with linked economic fundamentals, peer momentum should also exist in alternative linkages discovered in previous literature. In this section, we describe how to construct alternative linkages and their associated PM signals.

Industries: Firms in the same industry are natural candidates as peers that share similar fundamentals. We use the Text-based Network Industry Classifications (TNIC) developed in Hoberg and Phillips (2016) to define industries, which are based on the product market similarity disclosed in the firms' 10-Ks. Hoberg and Phillips (2016) demonstrates it to be more precise than the traditional SIC code-based industry classification.[4] The data are available from Gerard Hoberg's website and in yearly frequency.[5] We assume that the TNIC linkage in year T is available by the third Friday of June in year T+1. For each firm, other firms linked to it via TNIC linkage are defined as its industry peers, and the PM signal is the similarity-score-weighted average of peer returns.

Geography: Following Parsons et al. (2020), we obtain the zip code of firm's headquarter

[4]In unreported tests, we find that the TNIC-based industry momentum subsumes the industry momentum constructed following Moskowitz and Grinblatt (1999). Thus, we adopt the TNIC method.

[5]http://hobergphillips.tuck.dartmouth.edu/industryclass.htm. Following their suggestion, we use the TNIC-3 version.

location from Compustat and then group locations by economic areas, as defined by the Bureau of Economic Analysis (BEA)[6]. Firms located in the same economic areas are defined as geographic peers, and the PM signal is their equal-weighted average return.

Customers: We obtain data about firms' principal customers from the supply chain data in WRDS (the "wrdsapps.seglink" file). Similar to Cohen and Frazzini (2008), we assume that the customer data in calendar year T is available by the third Friday of June in year $T+1$. A firm's customer firms are defined as its customer peers, and the PM signal is again their equal-weighted average return.

Supplier and customer industries: Following Menzly and Ozbas (2010), we construct PM signals based on supplier- and customer-industry linkages. We use the open source asset pricing code provided by Chen and Zimmermann (2022) with input-output data from the BEA. For each industry, we obtain its supplier- and customer-industries at the BEA summary level. We follow Menzly and Ozbas (2010) and first calculate industry momentum as the equally weighted average of past option returns within each BEA industry. Then, for each firm, we calculate its supplier- and customer-industry PM signals as weighted averages of industry momentum across all its supplier- and customer-industries. The weight is the flow of goods or services from and to related industries, respectively.

Complicated firms: We obtain firms' business segment information from WRDS (the "compsegd.wrds_segmerged" file). Following Cohen and Lou (2012), we classify business segments at SIC 2-digit level, and keep those firms whose total sales from all reported segments account for at least 80% of its annual sales in Compustat. The conglomerate (standalone) firms are those firms operating in at least one (only one) industry. We assume that the segment information in calendar year T is available by the third Friday of June in year $T+1$. We then follow Cohen and Lou (2012) and again first compute industry momentum from

[6] In particular, we use the zip code to economic area mapping from Riccardo Sabbatucci's website: https://sites.google.com/site/riccardosabbatucci/Research

standalone firms before constructing a PM signal for each conglomerate firm as the weighted average of industry momentum across all the conglomerate's industry segments. The weight is the percentage of sales of each industry segment within the conglomerate.

Technology: We obtain firms' patent data, as in Kogan et al. (2017).[7] Following Lee et al. (2019), we first create a patent vector for each firm from the proportional shares of patents across different technology classes over the past five years. We then measure the technological closeness between firms as the cosine similarity of their patent vectors. The technological closeness is calculated in each calendar year T based on patent grant date over the past five years, and we assume that it is available by the third Friday of June in year $T+1$. The corresponding PM signal is the weighted average of all other firms' past option returns, with the weight proportional to the technological closeness measure.

LightGBM: For peers identified from LightGBM method, we follow Geertsema and Lu (2023) in selecting peers for each focal firm as those with the highest scores in the LightGBM method on the portfolio formation date. This implementation uses the option sample without requiring positive open interest.[8] We use 209 charateristics from Chen and Zimmermann (2022), which are cross-sectionally standardized, to predict $\log(IV)-\log(HV)$ and identify corresponding peer firms with LightGBM.[9][10]

[7] The data is available from: https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

[8] For each portfolio formation date and focal firm, we match the number of peers to the analyst-based method's average peer count for that period. We implement the LightGBM method using five-fold cross-validation to determine optimal hyperparameters, then apply the identified parameters to the entire cross-section to identify peer firms.

[9] The characteristics are sourced from `https://github.com/OpenSourceAP/CrossSection`. We winsorize them at the 1% and 99% levels and replace missing values with cross-sectional medians.

[10] Suggested by Geertsema and Lu (2023), tree-based prediction methods proceed by finding a sequence of rules that allocate training observations to groups in such a way that the group average valuation multiple is a good predictor. As a result, observations allocated to a particular group have an intuitive interpretation as "peer firms" in relation to the prediction firm.

To predict valuation multiples, we follow Geertsema and Lu (2023) to use LightGBM, a gradient boosting machine (GBM) implementation that combines sequentially constructed trees into a single model. A GBM model consists of a collection of trees (aka an ensemble of trees). The model is constructed by iteratively adding new trees to the GBM. Each newly added tree is trained on the residuals of the current model. For each tree, firms that fall into the same leaf node as the focal firm are assigned a certain weight. By aggregating these weights across all trees, we identify the peers of the focal firm as those receiving the highest

KMeans: We follow Seyfi (2022) to identify peer firms with the closest distances using the K-means method. This selects peers with characteristics most similar to those of the focal firm, where we again use the 209 characteristics from Chen and Zimmermann (2022).[11]

Composite: Firms are classified as peer firms under this method if they are connected through any of the above linkages. The weight assigned to each peer firm is determined by the number of times it is identified as a peer across all the above linkages.

2.5 Additional option return predictors

The choice of control variables largely follows Heston et al. (2023). We use the log market capitalization on the third Friday. Following Cao and Han (2013), we calculate idiosyncratic volatility as the standard deviation (annualized) of the residuals of a 22-day rolling regression using Fama-French 3 factors. To measure the slope of implied volatility term structure (IV term spread) in Vasquez (2017), we take the difference between the 60-day and 30-day ATM implied volatilities extracted from the Volatility Surface database; We measure the smirk of the implied volatility curve (IV smirk) as the difference between the implied volatility of a 30-day call with delta of 0.3 and that of a 30-day put with delta of -0.3. To get the volatility difference in Goyal and Saretto (2009) (IV - HV), we take the log difference between ATM implied volatility in the straddle and the rolling one-year historical volatility computed from

cumulative weights.

[11]Following Seyfi (2022), we assume that a stock's expected return is a function of its lagged characteristics. Formally, the framework posits that stock j's return at time t, denoted $r_{j,t}$, will exhibit similar behavior to the return of stock j_0 at time $t-1$ ($r_{j_0,t-1}$) if stock j's time-($t-1$) characteristic vector, $\mathbf{X}_{j,t-1}$, closely resemble stock j_0's time-($(t-2)$) characteristic vector, $\mathbf{X}_{j_0,t-2}$. The proximity between two stocks is measured by the Euclidean distance between their characteristic vectors:

$$d(j(t), j_0(t-1)) = \left[(\mathbf{X}_{j,t-1} - \mathbf{X}_{j_0,t-2})^\top (\mathbf{X}_{j,t-1} - \mathbf{X}_{j_0,t-2})\right]^{1/2} \tag{2}$$

where $d(j(t), j_0(t-1))$ quantifies the distance between stocks j and j_0 based on j's time-($t-1$) characteristics and j_0's time-($t-2$) characteristics.

We employ the `KNeighborsRegressor` algorithm from Python's `sklearn.neighbors` library to compute the pairwise distances between all firms in our sample. The neighboring assets for each focal firm are identified as those with the smallest computed distances, where the number of neighbors k is selected to match the count of analyst-based peers. We compute the peer momentum measure for each focal firm j at time t as the inverse-distance-weighted average of neighboring assets' lagged returns.

daily stock returns. Volatility of volatility (VOV) is computed as the standard deviation of the daily percentage changes of 30-day ATM implied volatilities over the past 22 trading days as in Cao et al. (2023). Finally, we also control for the firm's own momentum, either over a one-month ($MOM1$) or 12-month ($MOM12$) formation period.

2.6 Summary statistics

Table 1 describes our sample, which in this table is pooled across firms and dates. With about 540,000 straddle returns over the 1996-2024 period, the sample includes about 1,500 firms per month. The average straddle return is -4.9% per month, with a standard deviation that is nearly 40%. Distribution quantiles suggest positive skewness, as expected for a long options portfolio.

Firms in our sample have, on average, 101 peer firms with which they are connected via shared analyst coverage. Given that these firms have listed options with sufficient trading activity, they tend to be larger than average, with an average market capitalization of around $12 billion. Options on these firms tend to trade at implied volatilities (IVs) that are slightly lower than realized. They also have two-month implied volatilities that are on average lower than their one-month IVs, leading to a negative average IV term spread. OTM put IVs are higher than OTM call IVs, consistent with negative risk-neutral skewness.

Table 2 contains statistics on our main analyst-based peer measure as well as the alternatives discussed above. It differs from Table 1 in that the values reported are time series averages of cross-sectional statistics. The table shows that in the average month, the median firm has 67 peers connected to it through at least one common analyst. On average, there are 1,535 focal firms in our sample. These are the firms whose options pass the filters above and that have at least one peer. There is wide variation in the number of peers, with some focal firms just having one and others with hundreds.

Other peer linkages are often more limited in terms of fewer focal firms or fewer peers.

The “complicated” linkages, for example, apply only to focal firms that are multi-sector conglomerates. The median number of customer linkages is just one, owing to the sparse supply chain data in WRDS. Nevertheless, most alternative linkages are available for the majority of the focal firms we analyze using our analyst-based peer measure, and almost all linkages cover the entire sample or close to.

Some linkages result in many more peers than our primary measure. Customer- and supplier-industry linkages, for example, result in all firms in a given industry being selected a peers. The light GBM method results in all firms being selected as peers of all firms, though the weight that each peer firm receives in constructing the PM signal varies greatly across focal firms.

3 Main results

Our analysis begins with simple univariate sorts, in which we examine peer momentum and “standard” momentum using several different formation periods. After additional exploration of the formation periods, we then turn to the task of separating the two types of momentum and controlling for alternative return predictors. Next, the section examines robustness to transactions costs and the method of straddle return calculation. This is followed by an analysis about the importance of investor attention and alternative peer linkages. The section concludes with an alternative characterization of peer momentum based on realized and implied variances.

3.1 Peer momentum returns

Panel A of Table 3 shows strong evidence of peer momentum in univariate sorts. Ranking firms into equally-weighted quintile portfolios each month, we find strongly increasing relations between PM signals and future returns. The relationship is strong for formation periods ranging from one month to two years, though a conventional one-year formation period seems to perform the best. The t-statistics in parentheses, which are Newey-West adjusted with 3 lags, all indicate high levels of significance. The PM12 signal, for example, results in a return spread of 5.67% per month, with a corresponding t-statistic of 14.68.

While the relationship between PM signals and future returns is monotonic, we note that the biggest contribution to the high-low return spread comes from the bottom two quintiles. If we interpret the peer momentum effect to be the result of underreaction, which Heston et al. (2023) suggests to be the reason for option momentum, this implies that investors are mostly failing to recognize the tendency for spillover effects in lower-than-expected volatility, which is what tends to produce low option returns.

Panel B presents comparable results based on standard or "own" momentum. These results are slightly stronger but surprisingly similar. In particular, momentum is found using a variety of formation periods, including the shortest.[12] Notably, a large fraction of the momentum spread also arises from the difference between the bottom two quintiles.

Heston et al. (2025) shows that option momentum is strongest at seasonal lags. In particular, option returns that are multiples of three months prior to the holding period are more predictive than those at other lags. They show that this appears related to seasonality in the volatility arising from analyst forecast updates. Panels C and D of Table 3 compare the importance of seasonal lags for peer and own momentum, respectively.

Panel C shows that a PM signal constructed only from lags 3, 6, 9, and 12 results in a return spread of 5.18%. This is modestly higher than the returns spread of 4.56% offered by the strategy that uses the PM signal based on lags 1, 2, 4, 5, 7, 8, 10, and 11. In contrast, Panel D shows that own momentum strategies based on seasonal lags are around 34% more profitable than corresponding strategies based on non-seasonal lags. Similar patterns hold for the 24-month formation period. Thus, while there is some evidence of seasonality in peer

[12]Heston et al. (2023) documents reversal in one-month straddle returns. The current analysis differs due to our use of daily rebalancing in the straddle's delta hedge. Heston et al. (2023) discusses the impact of this choice, and we later examine non-rebalanced hedges for robustness.

momentum, it is comparatively minor. For the remainder of the paper, we will therefore not distinguish between seasonal and non-seasonal lags.

Table A1 examines the predictive content of PM signals computed over formuation periods from one to 60 months prior to the holding period. There is ample evidence of peer momentum at all horizons, though the inclusion of controls weakens the PM signal when the formation period is longer than 12 months. For this reason, our remaining results focus on just two formation periods, namely one month and one year.

3.2 Controlling for and comparing with other predictors

We next examine whether the predictability stemming from the PM signal can be explained by option momentum or other option return predictors. We also compare the economic magnitude of PM-based predictability with that of other option return predictors.

Our first results in this direction focus on distinguishing peer momentum from own momentum. We first do so by performing independent bivariate tercile sorts by option momentum and PM signals in each month. Panel A of Table 4 reports results for a sort based on a one month formation period, while Panel B uses 12-month formations.

The table shows that PM and own momentum each contain independent information. Controlling for own momentum, the high-low PM portfolio always delivers a significantly positive return. Likewise, when we control for peer momentum, own momentum remains significantly profitable. The two signals therefore appear to be distinct.

To control for additional option return predictors together, we rely on Fama-MacBeth regression. Table 5 presents the results, again using one-month and 12-month formation periods. In addition to own momentum (MOM), we control for size, idiosyncratic volatility (Cao and Han 2013), the IV term spread (Vasquez 2017), the IV smirk, the log difference between implied and historical volatility (IV-HV; Goyal and Saretto 2009), and the volatility of volatility (VOV; Cao et al. 2023).

The results, in Table 5, show that peer momentum remains robust to the inclusion of additional controls. For example, when we include both $PM1$ and $MOM1$, shown in column (2), $PM1$ remains highly significant, with a similar coefficient estimate and t-statistic to the univariate regression values reported in column (1). This is consistent with the previous double-sort results showing that peer momentum is only weakly related to own option momentum. In columns (3) and (4), we include other option return predictors documented in the literature, and peer momentum remains highly significant. The results are qualitatively the same when we use past 12-month returns for the PM signal, as seen in columns (5) to (8). Though the coefficients on $PM12$ decrease to some extent after we include more controls, they remain highly significant. Overall, PM appears to be a robust finding that is distinct from previous results in the literature.

Lastly, columns (9) and (10) show the effect of adding both the $PM1$ and $PM12$ signals to a regression that includes other predictors, including both short-term and long-term momentum. Both PM signals are significant, suggesting that multiple formation periods may be necessary to capture all the information in peer returns. Alternatively, it may be that an exponentially weighted PM signal, which puts more weight on more recent past returns, would perform better.

Turning next to the economic magnitude of peer momentum, we compare the long-short PM portfolio relative to those constructed from existing option return predictors in the literature. Table 6 presents various measures of performance evaluation.

The most competitive PM-related strategy is based on the past 12 months. This strategy has an average monthly return of 5.67% and a monthly Sharpe ratio of 0.87. The Sharpe ratio is lower than that of the corresponding 12-month option momentum strategy (1.16) and IV-HV (1.38), but it is higher than those of the strategies formed by firm size, idiosyncratic volatility, IV smirk, and volatility of volatility, and it is almost identical to the Sharpe ratio obtained from the IV term spread.[13] Overall, its economic magnitude is comparable with other well-documented option return predictors. In addition, the strategy formed by 12-month PM has a positive skewness of 0.62 and a maximum drawdown (the largest fraction by which the cumulative value of a portfolio falls below its prior maximum) of 13.61%. The PM strategy's downside risk is therefore less than that of option momentum, which is negatively skewed in this sample and that has a maximum drawdown that is more than twice as large. Thus, there is no evidence that the profitability of peer momentum can be explained by its exposure to tail risk.

To assess the stability of PM strategies, we examine 5-year moving averages of the returns on strategies formed by 1-month and 12-month PM. Figure 1 shows that 1-month PM has positive moving averages during the entire sample period, even though its profitability occasionally becomes insignificant. In contrast, the moving averages of past 12-month PM remain positive and significant during the entire sample period. In addition, its profitability tends to increase toward the end of the sample, and it appears to be more profitable in periods with high market-wide uncertainty, such as the Dot-com bubble, the Financial Crisis, and the COVID period. It is possible that investors' attention to firm-specific volatility information could be more limited at these times.

3.3 Alternative straddle returns

Our main results are constructed using "dynamic straddles", in which a constant straddle position is dynamically hedged by trading the underlying stock to maintain a zero total delta. The hedge is rebalanced daily, which results in monthly returns that have lower standard deviations and that are more highly correlated with approximated variance swaps (Heston et al. 2025). The literature is divided between studies that use such rebalancing and those

[13]To facilitate comparison among strategies, we have already adjusted the signs of all investment signals such that their long-short spreads are positive. For example, idiosyncratic volatility and IV-HV negatively predicts straddle returns. So we sort portfolios by the negative of idiosyncratic volatility and IV-HV.

that use a static delta hedge. The short-run momentum reversal strategy analyzed by Heston et al. (2023) is one example of where these two return concepts provide meaningfully different results.

We therefore reexamine our main results using two different approaches for computing straddle returns, which are used both for the strategy returns and the peer momentum signals. One is the static straddle. The other is a bias-adjusted dynamic straddle, which is constructed to avoid the microstructure biases discussed by Duarte et al. (2024) and Eberbach et al. (2025). This bias adjustment simply requires the delta used for hedging the straddle to be lagged one extra day, reducing any spurious correlation between noise in the underlying stock price and the option's delta, which is computed based on that price. Note that the static straddle, which does not update its hedge ratio, is naturally almost completely free of this bias.

Panel A of Table 7 shows the high-minus-low return spread from quintile portfolio sort based on each type of straddle return. Formation periods range from 1 to 24 months.

Overall, we find similar results for our benchmark dynamic straddle returns and for those constructed using the bias adjustment of Eberbach et al. (2025). In fact, bias adjustment slightly increases return spreads, though it marginally reduces their significance. The static straddle, in contrast, produces weaker results, particularly for shorter formation periods, for which long-short return spreads are insignificant.

As noted above, the dynamic and static straddles differ both in terms of their holding period returns and in the peer momentum signals they produce. Since the static straddle is more volatile due to its use of a crude hedge, it is natural to expect that it would produce a noisier PM signal. Indeed, in untabulated results we find that if a portfolio of static straddles is formed on the basis of a PM signal from dynamic straddles, its long-short returns are somewhat closer to the dynamic straddle portfolio. Similarly, the slight advantage that the bias-adjusted dynamic straddle has over the standard dynamic straddle appear to be due to the superiority of the bias-adjusted PM signal rather than the use of bias-adjusted returns in the holding period.

Panel B of Table 7 examines the correlation between each type of straddle return and the return on a synthetic variance swap, defined (as in Heston et al. (2025)) as the sum of squared daily returns over the holding period of the straddle divided by the implied variance at the start of the holding period, minus one. A higher correlation between straddle returns and synthetic variance swap returns indicates that the straddle is a better proxy for variance shocks.

Panel B reports average cross-sectional correlations between each type of straddle return and the returns on synthetic or approximated variance swaps. Using our benchmark dynamic straddle portfolio gives the highest average correlation, at 0.771, while the static straddle's average correlation is just 0.419. Using the bias-adjusted dynamic straddle is a little lower than our main measure, with an average correlation of 0.661, suggesting a potential downside of bias adjustment. We conclude that the standard dynamic straddle return is a reasonable proxy for volatility information, motivating our analysis of implied versus realized variance in Section 3.7.

Overall, Table 7 demonstrates that our main results are not driven by microstructure bias. They also show that peer momentum is robust, at least for longer formation periods, for the most common implementations of straddle returns, though the standard dynamic straddle return is most effective in capturing the volatility risks inherent in options.

3.4 Transactions costs

So far, our results assume that options can be bought and sold at the midpoint of the bid and ask quotes. To evaluate how bid-ask spreads affect profitability, we consider costs that are a fixed fraction of the quoted half-spread. The choice of fractions follows Muravyev and Pearson (2020): "Algo" traders pay 20.3% of the half-spread; "Adjusted" and "Effective" pays 51.6% and 75.8%, respectively, of the half-spread; "Quoted" refers to the case in which traders pay full quoted spread and buy options at the ask and sell at the bid. As an attempt to reduce the impact of bid-ask spreads, we also consider long-short strategies based on extreme deciles instead of quintiles as well as strategies that only include straddles whose percentage bid-ask spreads are in the lowest quartile in each month.

Table 8 presents the average monthly returns of the analyst-based long-short strategies under different spread ratios. In Panel A, which uses 1-month PM, our primary quintile-based strategy is unprofitable even for Algo traders. Using deciles increases the return spread, but still not enough to offset transactions costs. Only when we combine deciles with only trading low-cost straddles do we find positive returns after transactions costs, and that is only under the Algo case, in which those costs are lowest.

In contrast, our baseline 12-month PM strategy is significantly profitable for Algo traders. Furthermore, a decile-based strategy that only trades low-cost straddles remains profitable even assuming that traders pay the quoted spread. Assuming that investors pay effective spreads results in a return (2.62%) that is about half that of our baseline strategy (5.67%) and still highly significant (t-stat of 3.27). Thus, while reducing transaction costs is essential for the implementation of peer momentum, the strategy remains profitable under realistic assumptions.

3.5 Peer momentum and attention

In this section, we investigate the pervasiveness of peer momentum among groups of focal and peer firms with varying levels of investor attention. There are several motivations for our investigation. First, our findings would be of greater economic relevance to academics and practitioners if they are not confined to a small subset of focal and peer firms. Second, a confirmation of findings in most or all of the focal and peer firms would mitigate any concerns about data snooping driving our results. Third, if the mispricing is the explanation and is due to an underreaction to peer information, as we believe, we should expect greater peer momentum among focal firms or from peer firms with lower investor attention since information is likely to be disseminated less effectively for these firms.

We base this analysis on four proxies for investor attention: analyst coverage, firm size, option volume, and Google search volume. Analyst coverage in a given month is the number of analysts who have provided at least one FY1 or FY2 earnings forecast for the stock over the past 12 months. Size is the stock's most recent market equity capitalization. Option volume is the number of contracts traded in the most recent month on all the options written on the stock scaled by the average of the same value over the past 12 months. Following Da et al. (2011), our most direct measure of investor attention is Google search volume. For this we use the Search Volume Index (SVI) from Google Trends, a monthly index that reports how frequently Google users search individual stocks.[14] If sluggish incorporation of peer information is the cause of peer momentum, we would expect stronger momentum spillover from peer firms and to focal firms scoring lower on all these measures of investor attention.

Table 9 reports double sorts that examine the relationships between peer momentum and characteristics of focal or peer firms. In panel A, we begin by sorting focal firms into halves based on the characteristic at the head of the column. Within each half, we then form quintile peer momentum portfolios in the standard way, using either a one-month or a 12-month formation period. The table reports the high-minus-low quintile spreads of the low characteristic half and the high characteristic half. It also reports the difference between the high-minus-low spreads formed based on the two halves.

For example, the first column in panel A indicates that the high-minus-low peer momen-

[14]We download monthly Search Volume Index (SVI) for individual stocks from Google Trends. To do so, we search for stocks by their tickers, excluding those with ambiguous meanings, e.g., one-letter tickers and those having other meanings such as CAT, CATS, GATE, etc. As SVI is a standardized volume that reports the search volume relative to a benchmark value rather than the raw search volume, where the benchmark value can vary depending on the way SVI is downloaded, we adjust SVI for all stocks so that the same benchmark value is used to ensure comparable SVI both cross-sectionally and in the time series.

tum portfolio, when computed only among focal firms with low analyst coverage, has a mean of 3.23%. The same strategy computed from focal firms with high analyst coverage has a mean return of 2.35%. Both of these values are highly significant, with t-statistics above 5. Their difference, -0.88%, is significant and consistent with our attention hypothesis.

The same pattern is present in most of panel A. Peer momentum is pervasive across all sample splits and highly significant. It is also usually stronger in low attention focal firms, and these differences are mostly significant. An exception is for option trading volume, which is positively related to peer momentum profits, going against the hypothesis that low attention leads to higher peer momentum returns.

Using our most direct measure of investor attention yields the strongest results. When Google search volume for the focal firm is high, peer momentum profitability drops by about half. Furthermore, the difference between high- and low-search focal firms is highly significant. This pattern is present for both formation periods.

In panel B, all portfolio sorts include all focal firms. However, each focal firm's peers are now split into halves based on the same characteristics. That is, panel B reports the means of standard high-minus-low quintile spread portfolios, but now the PM signal is based on only half of each focal firm's peers.

Thus, the first column in panel B reports that a one-month PM signal constructed only from peers with relatively low analyst coverage results in a mean of 2.71% per month, while the PM signal based on peers with high analyst coverage results in a mean of 2.36%. The difference of -0.34% is statistically insignificant. Overall, peer momentum is again highly significant for all subsamples considered. Attention effects are weaker overall when sorting peers, though low attention peers are nevertheless significantly more predictive in half the cases. Notablely, the effects of Google search volume are much weaker for peers than for focal firms.

Overall, Table 9 shows that peer momentum is pervasive in the cross-section of both focal and peer firms' straddles, highly significant in focal and peer firms with both low and high attention. Moreover, there is some evidence that suggests underreaction to low-attention peers or, more strongly, by low-attention focal firms as a driving source. This is consistent with an explanation based on mispricing rather than time-varying risk premia.

3.6 Alternative peer connection measures

There are many possible notions of what constitutes a peer firm, many of which are listed in Section 2.4. In the literature on peer momentum in the equity markets, Ali and Hirshleifer (2020) find that peer momentum constructed from analyst coverage subsumes signals based on other peer concepts. While this was the motivation for our own use of analyst coverage in this paper, the superiority of analyst-based peer momentum in an option context has not been established. We therefore examine alternative peer definitions here and compare them to the analyst-based approach.

For each peer definition, we construct a different PM signal, including the composite signal, which combines all linkages. Table 10 shows the results in which these signals are used to predict straddle returns alone, together with the analyst-based PM signal, or together with the analyst-based PM signal and the set of control variables used in Table 5. Panel A examines a one-month formation period for each PM signal, while Panel B uses 12 months.[15]

The left-most columns in Panel A indicate that peer momentum is statistically significant for 7 out of the 9 alternative PM signals and for the composite signal. Overall, our analyst-based signal performs relatively well. It is only surpassed, either in terms of statistical significance or adjusted R-squared, by the two signals based on machine learning (Light GBM and K-means) and the composite signal. In particular, the composite measure has almost twice the adjusted R-squared of the analyst-based signal.

[15] In regressions with additional controls, the own momentum signal that is included uses the same formation period as the PM signal.

The middle columns of Panel A show bivariate regressions that include analyst-based PM as well as one of the 10 alternative measures. Analyst-based PM remains significant in all of these regressions except the one that includes the composite signal. The alternative PM signal is significant in 6 out of 10 cases. Adding additional controls has little effect on these results, as seen in the right-most columns of the table.

Panel B examines the 12-month formation period. In this case, univariate regressions indicate that all but one peer definition leads to a significant PM signal, though the analyst-based PM signal is the strongest, aside from the composite signal. The analyst-based PM signal remains significant in all bivariate regressions, including the one that includes the composite signal, with the alternative PM signal remaining statistically significant about half the time. Similar results are obtained when we include additional predictive variables as regressors.

Overall, these results confirm the strength of analyst-based peer momentum relative to other forms, reinforcing the conclusions of Ali and Hirshleifer (2020). Different from that study, however, many other forms of peer momentum offer incremental predictive power relative to analyst-based peer momentum. Shared analyst coverage is important, but it is not the same unifying force that it appears to be in stocks.

3.7 Variances, implied variances, and peer momentum

If straddle returns proxy for volatility information and limited attention to volatility information is the cause of option return predictability, then peers' past straddle returns should contain information that predicts realized variance (RV) and that is not fully incorporated into option markets. In this section, we use PM signals to predict realized variance across stocks. To check whether option markets respond to peer volatility, we also regress implied variance (IV) on PM signals. To further examine whether option markets can absorb peer volatility information, we use PM signals to predict the log difference between RV and IV, which is approximately equivalent to the log variance swap return.

Table 11 presents the results of Fama-MacBeth regressions. Panel A begins by showing that the one-month PM signal significantly predicts log RV, with a coefficient of 0.62 and a t-statistic of 4.73. Controlling for the firm's own lagged one-month straddle return, in column (2), has almost no effect on the PM coefficient or its significance and adds little to the explanatory power of the regression. Adding the firm's own lagged IV to the regression reduces the PM coefficient's magnitude but increases its significance, suggesting that option markets do not fully absorb peer volatility information.

When we instead use PM to predict log IV in column (4), the coefficient on PM is less significant and equal to 0.26. This implies that option markets respond to peer volatility information, but the fact that this coefficient is smaller than the value, 0.62, in column (2) tells us that option markets do not fully incorporate the information from peer volatilities. This is further confirmed when we predict the approximated log variance swap return, in column (5), where the coefficient on PM is large and highly significant. This explains the option return predictability. In Panel B, we repeat the above exercises with the one-year PM signal and one-year own momentum controls. Results are qualitatively similar.

4 Distinguishing peer from factor momentum

For both equity and option markets, recent papers (Ehsani and Linnainmaa 2021, Gupta and Kelly 2019, Käfer et al. 2025, and Beckmeyer et al. 2023) document strong factor momentum and argue that factor momentum can explain momentum primarily or even entirely. Further, Yan and Yu (2023) point out that peer momentum can also arise from factor momentum, with momentum spillover in the non-systematic or residual portion of returns being the other possible source. In this section we distinguish peer momentum in residual returns from factor momentum using two different approaches.

4.1 Systematic vs. residual momentum

In the first approach, we adopt a specific linear factor model that allows us to decompose straddle returns explicitly into systematic and residual portions. If peer momentum is driven only by factor momentum, we would expect only the momentum in the systematic portion of peer returns to be predictive of future focal returns. In contrast, if it is due to residual momentum spillover, then the residual portion should be predictive.

We choose a factor model based on the IPCA approach of Kelly et al. (2019) and proposed by Goyal and Saretto (2024), who show that this model does an excellent job in explaining the profitability of a long list of equity option strategies. To construct the model, we follow Goyal and Saretto (2024) and adopt three factors without an intercept and utilize the same 46 firm characteristics (together with a constant) as instruments. The model is estimated on the full sample and then used to decompose straddle returns into systematic and residual portions.[16] We then calculate systematic and residual peer momentum signals by taking the averages of systematic and residual portions of peer returns over different formation periods.

The results we present are based on the full-sample estimation of the factor model and are therefore not implementable. We do so to tip the scale in favor of the factor model being able to explain the data, given our desire to rule out factor momentum as the sole

[16] We follow Kelly et al. (2019) and Goyal and Saretto (2024) to estimate the following model:

$$r_{t+1} = \beta_t F_{t+1} + \epsilon_{t+1} = (Z_t \Gamma_\beta) F_{t+1} + \epsilon_{t+1} \tag{3}$$

where r_{t+1} is an $N_{t+1} \times 1$ vector representing the period-$(t+1)$ returns of the delta-hedged portfolios, and Z_t is an $N_{t+1} \times L$ matrix of the characteristics (with $L = 46+1$). This model will be estimated with Alternating Least Square (ALS) method following Kelly et al. (2019). After estimating this model, $Z_t \Gamma_\beta F_{t+1}$ serve as the systematic part and the residual part is calculated as $r_{t+1} - (Z_t \Gamma_\beta) F_{t+1}$.

Following Kelly et al. (2019), we normalize the 46 non-constant characteristics by first ranking each characteristic for each period. The ranks are then normalized as follows:

$$Z_{\text{normalized},i,t} = \frac{Z_{\text{rank},i,t} - \min(Z_{\text{rank},i,t})}{\max(Z_{\text{rank},i,t}) - \min(Z_{\text{rank},i,t})} - 0.5 \tag{4}$$

where $Z_{\text{rank},i,t}$ denotes the cross-sectional rank vector for the i-th characteristic. Here, $\max(Z_{\text{rank},i,t})$ and $\min(Z_{\text{rank},i,t})$ denote the maximum and minimum ranks, respectively. By adopting this method, $Z_{\text{normalized},i,t} \in [-0.5, 0.5]$, which is used in all the IPCA analysis.

cause of peer momentum. Nevertheless, in untabulated results we repeat our analysis using expanding windows and obtain similar results, slightly more in favor of the importance of residuals over factors.

Panel A of Table 12 reports average high-low spread portfolio returns from quintile portfolios based on either systematic or residual components of peer momentum. For both the one-month and 12-month formation periods, both components are significantly predictive of future focal returns. For example, the profits from two portions of peer momentum are similar in levels of both economic and statistical significance for the 12-month formation period (4.49% when sorting on systematic PM vs. 4.17% when sorting on residual PM). Panel A also decomposes total strategy profits into the parts explained and unexplained by the IPCA factor model. While the systemaic component of the peer momentum strategy are large, they are largely explained by systematic PM (3.89% systematic vs. 0.59% residual returns for the 12-month formation period). In contrast, the residual component of the PM strategy is primarily due to the residual component of the PM signal (0.85% systematic vs. 3.32% residual for the 12-month formation period).

Panel B uses Fama-MacBeth regressions to predict focal straddle returns and the portions explained and unexplained by the IPCA factor model. It includes systematic and residual PM as predictors and controls for the same return predictors used in Tables 5. Again, the evidence confirms that both parts of peer momentum are strongly and distinctly predictive of future focal returns. Further, the predictive information contained in the systematic component of the IPCA model cannot explain peer momentum in model residuals. In particular, the coefficient on systematic PM is essentially zero for the 12-month formation period in Panel B3, in which the dependent variable is the residual component of returns. The residual PM signal, in contrast, has a large positive coefficient with a t-statistics of 7.98.

In sum, we find a strong momentum spillover in residual returns, which is distinct from factor momentum. Further, both systematic and residual sources of momentum spillovers are approximately of equal importance.

4.2 Peer momentum vs. the factor momentum of Käfer et al. (2025)

Table 13 examines whether peer momentum captures the same return variation as cross-sectional factor (CSF) momentum, or whether each strategy contains incremental information not captured by the other. For comparison, we also examine own-stock momentum, which Käfer, Mörke, and Wiest (2026) concluded was fully spanned by CSF momentum. Following that paper, we construct CSF momentum from 28 firm characteristics, where stocks are sorted into deciles each month to form long–short portfolios. The direction of each characteristic portfolio is selected using an expanding historical window, with 1996–1998 serving as the initial burn-in period. The regressions cover January 1999 through November 2024 and are estimated for formation periods of 1, 3, 12, and 24 months. Reported t-statistics are based on Newey–West standard errors with three lags.

Panel A asks whether CSF momentum spans peer momentum or own momentum. Peer momentum loads positively and significantly on CSF momentum at every formation horizon. The estimated loading ranges from 0.49 to 0.70, with t-statistics between 3.99 and 8.92. The overlap is greatest for the one-month formation period, for which CSF momentum explains 32.1% of the variation in peer momentum. The R^2 falls to approximately 22% at the three- and twelve-month horizons and to 12.7% at the 24-month horizon. Thus, peer momentum and CSF momentum share a substantial component, particularly when they are constructed using recent information, but they are far from identical.

The alpha estimates provide only limited evidence that CSF momentum fully spans peer momentum. At the one-month horizon, the peer-momentum alpha is 0.006, with a t-statistic of 1.78. For longer formation periods, peer momentum retains positive and statistically significant alphas after controlling for CSF momentum.

The evidence against CSF momentum spanning own momentum is stronger, contrary to Käfer et al. (2025). Own momentum has a positive and highly significant alpha in all four specifications, ranging from 0.0194 at the one-month horizon to 0.0408 at the 24-month horizon. The corresponding t-statistics range from 4.78 to 7.15. Own momentum also loads positively on CSF momentum at the 1-, 3-, and 12-month horizons, but the relationship is weaker than for peer momentum. These results indicate that own momentum contains an economically and statistically distinct component that is not captured by CSF momentum, especially at longer formation horizons.

Panel B reverses the regressions and asks whether peer momentum or own momentum spans CSF momentum. Neither does. When CSF momentum is regressed on peer momentum, its alpha is positive and highly significant at every horizon, with t-statistics between 6.85 and 10.73. The peer-momentum loadings are also positive and significant, confirming the shared variation documented in Panel A, but peer momentum does not eliminate CSF momentum's incremental return. The same conclusion holds when CSF momentum is regressed on own momentum.

Overall, the results indicate meaningful overlap among peer momentum, own momentum, and CSF momentum, but little evidence of complete spanning. The one notable exception is the one-month peer-momentum strategy, whose alpha relative to CSF momentum is only marginally significant. At longer horizons, however, both peer and own momentum retain significant incremental returns, while CSF momentum also retains significant alphas when the regressions are reversed. The broader conclusion is therefore that these strategies capture related but distinct sources of return predictability rather than representing alternative implementations of a single momentum effect. Untabulated results using time-series factor momentum are even less favorable to the proposition that factor momentum spans peer or own momentum.

4.3 Symmetric vs. asymmetric effects

A shortcoming of the approach taken above is that, while the factor models we adopt are very general, it is impossible to rule out that an alternative specification wouldn't deliver different results. This section addresses this shortcoming by building on the model-free methods of Kelly et al. (2023) and Yan and Yu (2023).

Kelly et al. (2023) considers an environment in which each firm generates a unique signal and in which the weight held in a given firm depends on the signals of all firms. If S_t denotes the vector of signals, which in our case will be a measure of past straddle returns, the portfolio weight vector is given by $w_t = L'S_t$. The return on the strategy is therefore $w_t'R_{t+1} = S_t'LR_{t+1}$, where R_{t+1} is the vector of individual asset returns at time $t+1$. As in Kelly et al. (2023), we cross-sectionally demean R_{t+1} to isolate cross-sectional return predictability.[17]

L is referred to as the "position matrix", as it translates the signal vector into the vector of portfolio weights or positions. It controls whether and how the strategy exploits return predictability using each asset's own signal versus cross-return predictability in which a position depends on other assets' signals.

For example, when the diagonal entry $L_{i,i}$ is positive and the signal S_t measures past returns, as is the case here, then $L_{i,i}$ essentially captures a standard momentum effect. When the off-diagonal entry $L_{i,j}$ is negative, the strategy is attempting to exploit a negative cross-predictive relation between the signal of asset j and future return of asset i, a cross-reversal strategy in which a high past return in asset j leads to a more negative position in asset i. When any diagonal or off-diagonal entry is zero, the strategy simply does not

[17] Using demeaned R_{t+1} ensures a zero-cost strategy, which can be interpreted in two equivalent ways: (1) each test asset corresponds to a long position in firm i hedged by a short position in the equal-weighted portfolio of all firms, thereby rendering each test asset zero-cost; or (2) since w_t and R_{t+1} are vectors, $w_t'(R_{t+1} - \bar{R}_{t+1}) = w_t'R_{t+1} - N\bar{w}_t\bar{R}_{t+1} = (w_t - \bar{w}_t)'R_{t+1}$. Thus, demeaning R_{t+1} is equivalent to demeaning the weight vector w_t, ensuring that portfolio weights sum cross-sectionally to zero.

attempt to exploit the particular own or cross-return predictability represented by that entry.

Kelly et al. (2023) show that the expected profit of the strategy based on the position matrix L is $E[w_t' R_{t+1}] = E[S_t' L R_{t+1}] = tr(L\Pi)$, where $\Pi = E[R_{t+1} S_t']$ denotes the so-called "prediction matrix." This unobserved matrix reflects the own and cross-asset predictive relation between signals and future asset returns in the true data generating process. The formula implies that the profit of the strategy depends on how successfully the position matrix L exploits the true predictive relation embodied in the unobserved Π matrix.

The cross-return predictive relations embedded in Π can be regarded as symmetric or asymmetric. In a symmetric relation, asset i's signal forecasts asset j's return as much as j's signal forecasts i's return. This results in the symmetric entries $\Pi_{i,j} = \Pi_{j,i}$. In an asymmetric relation, one asset's signal forecasts the other asset's return more or less than the reverse case, resulting in $\Pi_{i,j} \neq \Pi_{j,i}$.

Kelly et al. (2023) show that the total profit of the strategy based on L can be decomposed into the profits of two sub-strategies whose respective position matrices are symmetric and antisymmetric, i.e., $L = L^s + L^a$, where $L^s = \frac{1}{2}(L + L')$ and $L^a = \frac{1}{2}(L - L')$. They further prove that the profit of the symmetric (antisymmetric) sub-strategy relies only on exploiting the symmetric (antisymmetric) portion of the true predictive relation in Π.

We exploit these properties in a final attempt to distinguish peer from factor momentum. As argued in Yan and Yu (2023), factor momentum should cause a symmetric predictive relation in Π, while momentum spillover in the residual returns can lead to both symmetric and asymmetric predictive relations in Π. The implication is that the symmetric portion of Π reflects both factor momentum and any symmetric momentum spillover in residual returns, while the asymmetric portion reflects only asymmetric momentum spillover in residual returns.

A linear trading strategy, which is defined by the choice of L matrix, will exploit cross-stock predictability when it aligns with the true Π matrix, in the sense that $tr(L\Pi) > 0$. If some of the strategy returns result from asymmetric momentum spillover in residual returns, as reflected in the asymmetric portion of Π, the profit from the corresponding antisymmetric sub-strategy based on L^a should be nonzero. It should be positive if the strategy aligns with the asymmetric momentum spillover in residual returns in the right direction and negative if in the opposite direction. As a result, we can test for the existence of the asymmetric portion of Π (and hence asymmetric momentum spillover in residual returns) by examining average returns on the L^a-based strategy. If these average returns are nonzero, factor momentum, which implies symmetric relations, cannot fully explain cross-stock lead-lag effects.

Importantly, the validity of this diagnostic does not rest on L being based on a consistent estimator of the true prediction matrix Π. For any implementable position matrix, expected profits satisfy $E[S_t' L R_{t+1}] = \mathrm{tr}(L\Pi) = \mathrm{tr}(L^s\Pi^s) + \mathrm{tr}(L^a\Pi^a)$, where the cross terms vanish because the trace of any symmetric matrix against an antisymmetric one is zero (Kelly et al., 2023, Lemma 2). For any L, the antisymmetric component's expected return, $\mathrm{tr}(L^a\Pi^a)$, is zero whenever $\Pi^a = 0$, regardless of how L is constructed.

A limitation of this approach is that it ignores the potential profitability of symmetric momentum spillover in residual returns. Given that we have no reason to expect mostly asymmetric effects in residual spillover, our focus on asymmetric effects surely understates the magnitude of this component of peer momentum returns. While this is a significant shortcoming, the benefit is that we do not need to impose any explicit factor model, as in our first approach to separating peer from factor momentum, in order to draw inferences.[18]

We operationalize this approach in several ways. In this section, we use this framework to understand the role of asymmetric effects in the analyst-based strategy we have explored, essentially assuming that the Π matrix can be recovered from analyst linkages as opposed

[18]Furthermore, even if peer momentum is entirely uni-directional in the sense that some firms lead others but not vice versa, the symmetric effect will still be nonzero. This is because the symmetric effect essentially captures the average level of cross-predictability, which will be nonzero under these assumptions. Thus, the asymmetric component will likely be no higher than 50% even if peer momentum is completely uni-directional, which would be inconsistent with factor momentum.

to historical lead-lag return patterns. In the next section, we compare the analyst-based peer momentum strategy with the purely data-driven approach of Yan and Yu (2023), which is modified to remove own-momentum effects. Lastly, we ask whether the data-driven and analyst-based approaches can be combined to achieve superior performance.

To recast our analyst-based strategy in the notation of Kelly et al. (2023), we construct a proxy of the prediction matrix (at a given point in time) as

$$\hat{\Pi}_{i,j} = \begin{cases} n_{i,j}/\sum_{j=1}^{N} n_{i,j} & \text{for } i \neq j \\ 0 & \text{for } i = j, \end{cases}$$

where $n_{i,j}$ is the number of analysts common to both the focal firm i and the peer firm j. We then set $L = \Pi'$. Like our baseline strategy, the resulting portfolio weight vector, $w_t = L'S_t$, directly captures a peer momentum signal based on analyst linkages. But the new strategy's return, $S_t'LR_{t+1}$, is constructed from the entire cross section, offering a more diversified alternative to the baseline sort-based strategy, which takes positions only in the extreme long and short quintiles.

The L matrices constructed in this way are asymmetric. Although it is the case that $n_{i,j} = n_{j,i}$, asymmetry arises because of differences in the denominators, as $\sum_{j=1}^{N} n_{i,j} \neq \sum_{i=1}^{N} n_{i,j}$.[19] The question is whether this asymmetry, which is inherent to our portfolio construction, is a desirable feature in the sense that it improves strategy performance. If not, this would suggest a potential shortcoming of our strategy and a rejection of our peer specification. If so, it would indicate that asymmetries, which are inconsistent with factor momentum, are important.

Table 14 contains the results of this analysis. We examine both the 1-month and the 12-

[19] As a simple example, suppose there are three firms. One analyst follows firm 1 and firm 2, while another follows firm 1 and firm 3. This yields $n_{1,2} = 1$, $n_{1,3} = 1$, and $n_{2,3} = 0$. The numerators of $\Pi_{1,2}$ and $\Pi_{2,1}$ are $n_{1,2} = n_{2,1} = 1$. But the denominator of $\Pi_{1,2}$ is $\sum_{j=1}^{3} n_{1,j} = 2$ while the denominator of $\Pi_{2,1}$ is $\sum_{j=1}^{3} n_{2,j} = 1$.

month formation periods, where the period determines the average return used to construct the signal matrix S_t. For each formation period, we compute total strategy profitability as well as the decomposition into symmetric and asymmetric components. Because weights produced by this approach are not normalized in any economically meaningful way, each strategy's weights are scaled by the same constant that makes the volatility of the total strategy returns match that of an equal-weighted portfolio of straddles.

The table shows that most of the return on each strategy arises from the symmetric component but that a statistically and economically significant contribution comes from the asymmetric component. Asymmetry is therefore an important aspect of our analyst-based peer specification, and it leads to a source of profitability that is inconsistent with factor momentum.[20]

The last row in the table measures the correlation between the strategy returns computed in this section, which are analyst-based but not the same as those of our baseline sort-based strategies from Table 3, with the returns on those sort-based baselines from Table 3. For the 12-month strategy, the correlation is very high, around 0.9. For the 1-month strategy, the correlation is a bit lower, at around 0.8. While not identical, the strategies examined in this section are therefore at least reasonably similar to our baselines.

5 Data-driven strategies and peer reversal

Our baseline analyst strategy uses economically motivated links to identify lead-lag return relations across firms, but it is implicitly designed to identify and trade only cross-momentum relations. An alternative is to estimate lead-lag relations directly from historical data, as in Yan and Yu (2023). Unlike the analyst-based approach, this data-driven (DD) approach can identify and trade both cross-momentum and cross-reversal, as determined solely by the

[20]Moreover, because of the possibility of symmetric peer momentum in residuals, which is not factor-driven, the contribution of the asymmetric component should be regarded as a lower bound on "pure" peer momentum.

relations estimated from past data.

In this section, we evaluate the DD approach and compare it with the analyst-based approach for three reasons. First, as Yan and Yu (2023) show in stocks, the firm linkages uncovered by the DD approach generate strong trading profits and explain most of the return predictability documented in prior cross-stock momentum studies. This evidence raises the question of whether the approach is similarly effective for trading equity options. Second, because the DD approach combines cross-momentum and cross-reversal, it has the potential to improve profitability. Third, the analyst-based approach assumes that every identified linkage exhibits cross-momentum. Although the strategy's positive profits suggest that this assumption generally holds, a subset of the identified firm linkages may nevertheless exhibit cross-reversal. If so, using the DD approach to identify these cross-reversal linkages could enhance the profitability of our baseline analyst strategy.

We implement the DD strategy within the Kelly et al. (2023) framework as follows. First, like Yan and Yu (2023), at the beginning of month t we estimate the prediction matrix Π as $\hat{\Pi}_{i,j} = \frac{1}{T}\sum_{\tau=t-T+1}^{t} R_{i,\tau}S_{j,\tau-1}$ using a 60-month rolling window and requiring at least 24 months of data, where S is the raw option momentum signal and R is the cross-sectionally demeaned straddle return. Second, after setting the diagonal entries of $\hat{\Pi}$ to zero, we set the position matrix L equal to $\hat{\Pi}'$. Setting the diagonal entries to zero ensures that the strategy exploits cross-firm relations rather than own-firm lead-lag relations, such as standard momentum effects. Each month, we move the estimation window forward by one month, update L, and compute the strategy return $S_t'LR_{t+1}$.

Although this procedure is theoretically implementable, it allows an arbitrary amount of leverage, making the economic magnitude of average returns difficult to interpret. As in Section 4.3, we therefore modify L so that the positions scale the overall volatility of strategy returns to match that of an equal-weighted portfolio of equity straddles.

Column "All L" of "DD" in Table 15 reports the profitability of the DD strategy. The strategy generates a significant positive monthly return of 5.2% (8.9%) and an annualized Sharpe ratio of 1.44 (2.47) for the 1-month (12-month) formation period. Its average returns and Sharpe ratios exceed those of the baseline analyst strategy (column "Baseline") implemented within the Kelly et al. (2023) framework for the 1-month formation period but not for the 12-month formation period. This higher profitability for 1-month formation period illustrates the potential gain from the DD strategy's ability to exploit both cross-momentum and cross-reversal relations, whereas the analyst strategy exploits only cross-momentum relations.

To assess how cross-momentum and cross-reversal relations contribute to the profitability of the DD strategy, we decompose it into two sub-strategies whose returns sum to that of the full DD portfolio. One sets the position matrix to $L^+ = max(L, 0)$, and the other sets it to $L^- = min(L, 0)$. The monthly return to each sub-strategy is $S_t' L^{sub-strategy} R_{t+1}$, where $L^{sub-strategy}$ equals either L^+ or L^-. The former exploits only cross-momentum relations, whereas the latter exploits only cross-reversal relations. Columns "$L > 0$" and "$L < 0$" of "DD" in Table 15 report the profitability of these two sub-strategies. Both generate significant positive returns for both formation periods. The cross-momentum sub-strategy accounts for more of the main strategy's returns at the 12-month formation period, whereas the cross-reversal sub-strategy accounts for more at the 1-month formation period. These findings suggest that both types of lead-lag relation are prevalent in the data. The prevalence of cross-reversal uncovered by the DD approach is surprising because, to the best of our knowledge, the asset pricing literature has generally documented cross-momentum in cross-firm lead-lag relations.

Because the results suggest that the DD approach successfully identifies firm linkages that exhibit cross-reversal, we next ask whether accounting for these reversal linkages improves the profitability of the baseline analyst strategy. As discussed above, the analyst-based approach assumes cross-momentum for every linkage it identifies. It may therefore lose profits by taking an incorrect cross-momentum position on linkages that actually exhibit cross-reversal. Correcting or avoiding these positions should therefore improve the baseline analyst strategy. We implement this idea by constructing a data-driven-enhanced analyst (DDAW) strategy. For each focal firm, we begin with the peers identified by the baseline analyst strategy and divide them into momentum and reversal subsets. Peers in the first subset have positive corresponding entries with the focal firm in the DD approach's position matrix L, whereas peers in the second subset have negative entries. We then repeat the position-matrix construction for the baseline analyst strategy described in Section 4.3, separately using only the momentum or reversal subset for each focal firm. This procedure yields a position matrix L^+ for the momentum subset and a position matrix L^- for the reversal subset. We construct the final DDAW position matrix by summing the two matrices, $L = L^+ + L^-$. Accordingly, the DDAW strategy's profit equals the sum of the two sub-strategies' profits. This construction differs from that of the DD strategy, for which we first identify the main strategy's position matrix L and then derive the sub-strategy matrices. Finally, for the DDAW strategy, we again modify L so that the positions scale the overall volatility of strategy returns to match that of an equal-weighted portfolio of equity straddles.

We hypothesize that firms covered by more common analysts are more closely linked fundamentally and offer greater scope for underreaction and cross-momentum. Cross-reversal may therefore be more relevant for firm linkages covered by fewer common analysts. To incorporate this hypothesis into the DDAW strategy, we construct the position matrix for the momentum subset as in Section 4.3, weighting peers by the number of common analysts:

$$L^+_{i,j} = n_{i,j} / \sum_{j=1}^{N} n_{i,j},$$

where $n_{i,j}$ is the number of analysts who cover both focal firm i and peer firm j. For the reversal subset, we instead weight peers by the reciprocal of the number of common analysts:

$$L^{-}_{i,j} = -(1/n_{i,j})/\sum_{j=1}^{N}(1/n_{i,j}).$$

Using reciprocal weights places more weight on the past return signals of peers covered by fewer common analysts, potentially making cross-reversal more pronounced. The minus sign ensures that the entries in the position matrix L^{-} are negative and that the strategy takes positions consistent with cross-reversal.

Column "DDAW" in Table 15 reports the profitability of the DDAW strategy and its two sub-strategies. For the 12-month formation period, the DDAW strategy (column "All L") delivers higher average return and Sharpe ratio than the baseline analyst strategy; for the 1-month formation period, both measures are slightly lower. The momentum sub-strategy (column "$L > 0$") generates a significant positive return for both formation periods, while the reversal sub-strategy (column "$L < 0$") return is significantly positive only for the 12-month formation period. Overall, the evidence supports the value of incorporating the DD approach into the baseline analyst approach and highlights the importance of identifying peer reversal.

We also ask whether the DD and DDAW strategies and their cross-momentum sub-strategies contain information similar to that in the baseline analyst strategy, which exploits only cross-momentum. We regress the monthly returns of each DD or DDAW strategy or cross-momentum sub-strategy on the returns of the baseline analyst strategy. We then reverse these regressions, regressing the baseline analyst strategy's monthly returns on those of each DD or DDAW strategy or cross-momentum sub-strategy. Table 16 reports the results.

For both the 1-month and 12-month formation periods, significant positive alpha remains when the baseline analyst strategy is regressed on the DD or DDAW strategies and sub-strategies. Significant positive alpha also remains when the DD or DDAW strategies and sub-strategies are regressed on the baseline analyst strategy, with the exception that the DDAW full strategy and DDAW cross-momentum sub-strategy show only a marginally significant positive or a negative alpha when they are regressed on the baseline analyst strategy in the one-month formation period. The R^2 exceeds 70% in the reciprocal spanning regressions involving the analyst strategy and the DDAW cross-momentum sub-strategy. Overall, the evidence suggests that the DD and DDAW strategies and sub-strategies share information with the baseline analyst strategy about lead-lag return linkages but also contain distinct information.

5.1 Peer reversal: portfolio sorts

In this section, we present more evidence of peer reversal by adopting an univariate portfolio sort approach. Our portfolio sorts capture the spirit of the peer reversal portfolios evaluated in the $L < 0$ columns of Table 15. Specifically, we first use the negative entries in L employed by the DD or DDAW strategy to identify "reversal peers." Under the DD approach, these are firms whose historical returns are negatively related to a focal firm's future returns. Under the DDAW approach, they are firms that share common analysts with a focal firm and whose historical returns are negatively related to the focal firm's future returns. We then form a peer reversal signal for each focal firm using its set of reversal peers. These signals do not weight peers by the number of shared analysts. Instead, when reversal peers are identified using the DD approach, we weight them by the absolute value of the L estimate linking each peer to a given focal firm. When they are identified using the DDAW approach, we weight them by the reciprocal of the number of shared analysts.[21] We sort focal firms' straddles into quintiles by reversal signals and form equal-weighted portfolios. The resulting portfolios are therefore designed to capture DD or DDAW peer reversal in the Kelly et al.

[21] As in earlier results, the L matrix is estimated on a rolling out-of-sample basis using the most recent 60 months of data, which is why the sample begins in 2001.

(2023) framework as fully as possible. We report results for both 1-month and 12-month formation periods.

Table 17 reports the resulting quintile spreads. The table panel A shows that the DD peer reversal strategy is highly profitable and significant for both formation periods, generating an average quintile spread of approximately 3% and 5% per month. The DDAW peer reversal strategy in panel B reports only marginally significant profit at 0.53% per month for 12-month formation period and reports no reversal but significant momentum profit at 1.25% per month for 1-month formation period. Overall, results are consistent with Table 15 in the Kelly et al. (2023) framework and suggest that cross-reversal is mainly a phenomenon that exists outside of analyst-linked firm pairs.

6 Conclusions

Peer momentum is an important phenomenon in the options market, with a level of risk-adjusted profitability that ranks among the top performing option strategies. It is also distinct from those strategies, in that controlling for them has only a modest effect on the size and significance of the peer momentum effect. Its performance over time is quite consistent as well, with the strategy based on a 12-month formation period yielding positive and significant returns in each five-year period since the start of our sample.

Like Ali and Hirshleifer (2020), we find that peer links based on shared analyst coverage are particularly powerful. At the same time, most other methods for forming links result in significant peer momentum, and PM signals based on other links retain incremental predictive power even after controlling for analyst-based peer momentum. Thus, while analyst-based peer momentum is strong and robust, it does not subsume other forms of peer momentum, as Ali and Hirshleifer (2020) found to be the case in stocks.

An important but difficult question is whether peer momentum is a phenomenon separate from factor momentum. While it is likely that factor momentum plays an important role, a variety of results rule out factor momentum as a complete explanation. Using the IPCA approach of Kelly et al. (2019), we find that both systematic and residual returns exhibit peer effects. Peer momentum returns are also distinct from those of the option factor momentum strategy of Käfer et al. (2025). Lastly, using the principal portfolios method of Kelly et al. (2023), we find evidence of asymmetry in peer momentum, which is inconsistent with factor momentum.

A comparison between analyst-based and data-driven peer momentum shows that both strategies offer highly significant expected returns that are comparable in terms of Sharpe ratios. Neither strategy spans the other, suggesting economically distinct sources of return. The data-driven approach also reveals significant evidence of peer reversal, but this effect is largely absent among analyst-based firm links. Nevertheless, an analyst-based strategy can be improved by filtering out links associated with peer reversal.

Rather than being a single strategy, peer momentum is a class of strategies, and an optimal implementation is most likely more complex than the simple strategies presented here. For example, PM signals with one-month and 24-month formation periods generate long-short portfolio returns that have a time series correlation of just 0.35, yet both strategies are highly profitable. It therefore seems likely that a strategy that takes advantage of multiple formation periods or perhaps constructs a PM signal with exponentially decaying weights would improve upon those we present here.

Moreover, an optimal implementation of peer momentum must recognize that not all peer pairs exhibit positive lead-lag relations, as peer reversal is also apparent and highly significant in a minority of pairings. And while the principal portfolios approach of Kelly et al. (2023) can accommodate such peer reversal, it requires an extension to be able to address the likely importance of multiple signals and/or exponential decay. Expanding further in these directions should yield new insights and improved trading strategy performance.

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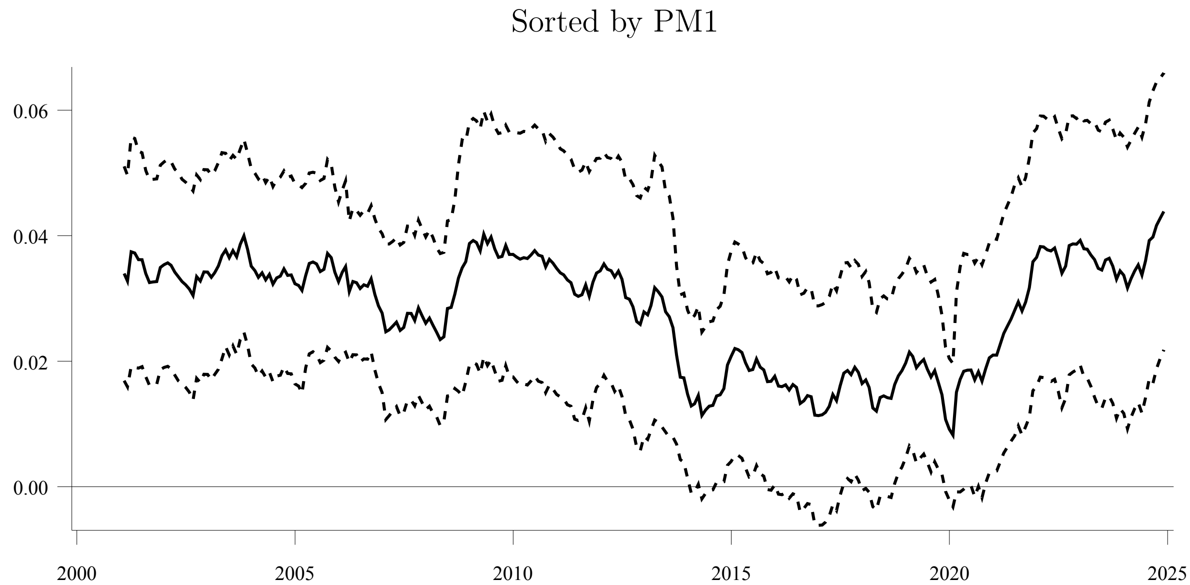

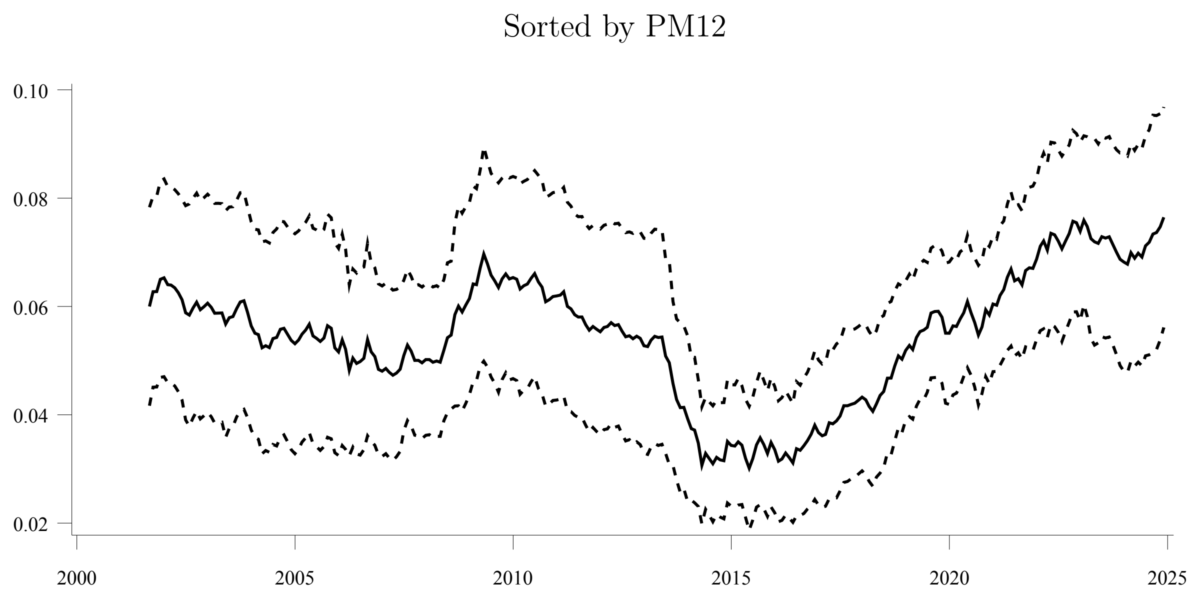

Figure 1: Five-year Moving Average Returns of Peer Option Momentum Strategy. This figure plots the rolling 5-year average returns of PM strategies (1-month formation period on the top panel, 12-month formation period on the bottom panel), along with the 95% confidence intervals in dashed lines. Standard errors are Newey-West adjusted with 3 lags.

Table 1: Summary Statistics

This table reports the summary statistics. Straddle return is at monthly frequency, and it is the excess return (over the risk-free rate) of an at-the-money straddle that is daily delta-hedged until expiration. Number of connected firms is the number of a firm's peers identified by shared analyst coverage and we restrict peers to firms with options. PM1, PM3, PM12, and PM24 are a firm's peer option momentum signals constructed with peers' past 1-month, 3-month, 12-month, and 24-month average straddle returns. MOM1, MOM3, MOM12, and MOM24 are the option momentum, defined as the average of a firm's straddle returns over the past 1, 3, 12, and 24 months. Market capitalization is a firm's stock market capitalization in billions of dollars. Idiosyncratic volatility is the standard deviation (annualized) of the stock return residuals from a 22-day rolling regression using Fama-French 3 factors (Cao and Han, 2013). IV term spread is the slope of implied volatility term structure (Vasquez, 2017) defined as the difference between 60-day and 30-day at-the-money implied volatilities. IV smirk is the smirk of implied volatility curve defined as the difference between the implied volatilities of the 30-day call with delta of 0.3 and the 30-day put with delta of -0.3. IV-HV is the log difference between at-the-money straddle implied volatility and historical volatility (Goyal and Saretto, 2009). VOV is the volatility of volatility defined as the standard deviation of the daily percentage changes of 30-day at-the-money implied volatility over the past 22 trading days (Cao, Vasquez, Xiao, and Zhan, 2023). Sample period is from January 1996 to November 2024.

	Observations	Mean	StdDev	P10	Median	P90
Number of firms per month	347 months	1557.88	230.34	1298	1564	1800
Straddle return	540585	-0.049	0.389	-0.414	-0.095	0.325
Number of connected firms	533175	100.75	98.74	36	81	158
PM1	531739	-0.042	0.155	-0.201	-0.064	0.134
PM3	530865	-0.042	0.099	-0.150	-0.054	0.072
PM12	525012	-0.043	0.056	-0.110	-0.046	0.028
PM24	516188	-0.042	0.044	-0.094	-0.044	0.014
MOM1	526893	-0.044	0.393	-0.417	-0.094	0.342
MOM3	524596	-0.045	0.231	-0.289	-0.071	0.216
MOM12	488815	-0.046	0.123	-0.190	-0.051	0.105
MOM24	447192	-0.045	0.092	-0.155	-0.046	0.068
Market capitalization (billions)	540585	12.090	54.928	0.363	2.237	23.053
Idiosyncratic volatility	540322	0.366	0.282	0.137	0.293	0.674
IV term spread	540566	-0.009	0.069	-0.067	-0.002	0.042
IV smirk	540566	-0.014	0.147	-0.101	-0.027	0.067
IV-HV	524576	-0.006	0.273	-0.318	-0.007	0.310
VOV	537098	0.074	0.076	0.028	0.054	0.134

Table 2: Summary Statistics on Peer Linkages

This table reports time-series averages of cross-sectional statistics for focal firms' peer counts by linkages, including the minimum, median, mean, maximum, and standard deviation. It also reports the average number of focal firms, which are firms that pass data filters and have at least one peer. The sample period during which each linkage is available is reported in the last two columns.

	Number of peers					Avg. # focal firms	Start date	End date
	Min	Median	Mean	Max	StdDev			
Shared Analyst	1	67	80	267	50	1535	1996/1/19	2024/11/15
Complicated	2	89	115	445	92	379	1996/2/16	2024/11/15
Customer	1	1	2	12	1	303	1996/1/19	2024/11/15
Customer Industry	10	511	451	1337	324	1182	1996/2/16	2024/11/15
Geography	1	77	89	222	72	1415	1996/1/19	2024/11/15
K-Means	50	50	50	50	0	1560	1996/2/16	2024/11/15
Light GBM	1971	1971	1971	1971	0	1512	1996/1/19	2024/11/15
Supply Industry	273	1338	1257	1488	276	1178	1996/2/16	2024/11/15
Technology	7	532	512	919	226	770	1996/1/19	2024/11/15
TNIC3	1	25	47	218	52	1418	1996/1/19	2024/11/15
Composite	97	319	332	698	81	1558	1996/1/19	2024/11/15

Table 3: Univariate Portfolio Sorts

This table presents the mean returns and t-statistics from univariate quintile sorts based on peer option momentum and own option momentum signals over different formation periods. For peer and own momentum signals, we also construct seasonal components using month lags at 3, 6, 9, etc., and nonseasonal components using month lags at 1, 2, 4, 5, 7, 8, etc. We form equally weighted portfolios on the third Friday of each month and hold to maturity. All returns are monthly and in percentages. T-statistics in parentheses are Newey-West adjusted with 3 lags.

Panel A: Peer momentum

	Low	2	3	4	High	High-Low
PM1	-6.70	-5.05	-4.57	-3.88	-3.74	2.96
	(-10.31)	(-6.88)	(-6.33)	(-5.18)	(-4.87)	(7.69)
PM3	-7.20	-5.15	-4.50	-4.03	-3.11	4.10
	(-10.49)	(-7.24)	(-6.19)	(-5.36)	(-4.04)	(10.09)
PM12	-8.16	-5.34	-4.40	-3.47	-2.49	5.67
	(-11.43)	(-7.18)	(-6.01)	(-4.61)	(-3.28)	(14.68)
PM24	-8.15	-5.21	-4.26	-3.78	-2.46	5.70
	(-11.45)	(-6.80)	(-5.69)	(-4.96)	(-3.08)	(13.72)

Panel B: Own momentum

	Low	2	3	4	High	High-Low
MOM1	-7.99	-4.93	-3.78	-3.26	-4.22	3.76
	(-11.64)	(-6.95)	(-5.36)	(-4.31)	(-5.49)	(9.21)
MOM3	-8.71	-5.44	-3.81	-2.75	-3.35	5.36
	(-12.47)	(-7.48)	(-5.19)	(-3.71)	(-4.45)	(13.38)
MOM12	-8.89	-5.42	-3.74	-2.78	-2.32	6.58
	(-12.19)	(-7.22)	(-4.92)	(-3.64)	(-3.13)	(16.24)
MOM24	-8.45	-5.20	-3.74	-2.67	-2.40	6.05
	(-11.50)	(-6.80)	(-4.70)	(-3.38)	(-3.13)	(15.34)

Panel C: Seasonal and non-seasonal peer momentum

	Low	2	3	4	High	High-Low
PM12 (seasonal)	-7.98	-5.17	-4.35	-3.51	-2.80	5.18
	(-10.85)	(-6.95)	(-5.76)	(-4.83)	(-3.80)	(14.85)
PM12 (nonseasonal)	-7.51	-5.21	-4.46	-3.67	-2.95	4.56
	(-10.34)	(-6.96)	(-6.16)	(-4.97)	(-3.85)	(11.73)
Difference						0.62
						(1.64)
PM24 (seasonal)	-8.12	-5.25	-4.10	-3.52	-2.80	5.32
	(-11.44)	(-6.64)	(-5.38)	(-4.69)	(-3.63)	(15.17)
PM24 (nonseasonal)	-7.54	-4.92	-4.44	-3.83	-3.07	4.47
	(-10.37)	(-6.51)	(-5.75)	(-5.00)	(-3.86)	(10.18)
Difference						0.85
						(2.28)

Panel D: Seasonal and non-seasonal own momentum

	Low	2	3	4	High	High-Low
MOM12 (seasonal)	-8.55	-5.48	-4.14	-2.90	-1.99	6.56
	(-11.63)	(-7.41)	(-5.34)	(-3.82)	(-2.70)	(19.04)
MOM12 (nonseasonal)	-8.07	-4.80	-3.91	-3.09	-3.19	4.88
	(-10.97)	(-6.49)	(-5.09)	(-4.09)	(-4.24)	(12.58)
Difference						1.68
						(5.03)
MOM24 (seasonal)	-8.17	-5.35	-4.14	-2.67	-1.82	6.35
	(-10.94)	(-6.97)	(-5.16)	(-3.38)	(-2.38)	(18.81)
MOM24 (nonseasonal)	-7.55	-4.64	-3.63	-3.12	-3.44	4.11
	(-10.28)	(-5.94)	(-4.63)	(-3.96)	(-4.36)	(10.24)
Difference						2.24
						(5.77)

Table 4: Double Sorts by Peer Option Momentum and Option Momentum

This table presents the results of double sort between peer option momentum and option momentum constructed with past 1-month and past 12-month straddle returns. On the third Friday of each month, we sort firms independently into terciles based on each variable. We then equally weight firms in each group and report their average returns (in percentage). T-statistics in parentheses are Newey-West adjusted with 3 lags.

Panel A: 1-month formation period

	Low PM1	Middle	High PM1	High-Low
Low MOM1	-7.45	-6.03	-6.29	1.16
	(-11.18)	(-8.23)	(-8.21)	(3.22)
Middle	-4.70	-3.59	-2.99	1.71
	(-6.65)	(-4.78)	(-4.07)	(5.62)
High MOM1	-5.23	-3.93	-2.85	2.38
	(-7.20)	(-5.07)	(-3.53)	(6.76)
High-Low	2.22	2.10	3.43	
	(6.11)	(5.83)	(9.57)	

Panel B: 12-month formation period

	Low PM12	Middle	High PM12	High-Low
Low MOM12	-8.88	-6.37	-6.10	2.78
	(-12.25)	(-8.37)	(-7.80)	(7.92)
Middle	-4.98	-3.76	-2.54	2.44
	(-6.38)	(-4.88)	(-3.33)	(7.93)
High MOM12	-4.75	-2.91	-1.13	3.62
	(-6.33)	(-3.84)	(-1.42)	(10.05)
High-Low	4.13	3.46	4.97	
	(11.51)	(10.73)	(13.81)	

Table 5: Fama-MacBeth Regressions

This table reports the coefficients of Fama-MacBeth regressions of straddle returns on peer option momentum signals and other characteristics. We focus on peer option momentum signals with 1-month and 12-month formation periods. T-statistics in parentheses are Newey-West adjusted with 3 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PM1	0.111	0.102	0.093	0.085						0.042
	(8.08)	(7.65)	(7.73)	(6.95)						(3.34)
PM12					0.545	0.405	0.340	0.346		0.302
					(17.23)	(12.65)	(10.43)	(10.75)		(9.11)
MOM1		0.011	0.030	0.020				0.024	0.024	0.022
		(3.62)	(10.49)	(6.35)				(6.88)	(7.02)	(6.91)
MOM12				0.099		0.146	0.091	0.076	0.106	0.077
				(10.62)		(15.22)	(11.39)	(8.65)	(11.69)	(8.87)
Ln(Market cap.)			-0.000	-0.001			-0.000	-0.002	-0.001	-0.002
			(-0.30)	(-1.13)			(-0.34)	(-1.47)	(-0.94)	(-1.42)
Idiosyncratic vol.			-0.096	-0.101			-0.081	-0.102	-0.101	-0.102
			(-11.04)	(-11.43)			(-10.63)	(-11.53)	(-11.03)	(-11.74)
IV term spread			0.121	0.153			0.159	0.161	0.152	0.161
			(6.42)	(7.89)			(8.15)	(8.13)	(7.85)	(8.20)
IV smirk			0.031	0.034			0.039	0.036	0.032	0.036
			(3.52)	(3.54)			(4.18)	(3.87)	(3.37)	(3.82)
IV-HV			-0.154	-0.133			-0.129	-0.131	-0.131	-0.132
			(-17.33)	(-13.99)			(-14.13)	(-13.89)	(-13.77)	(-13.95)
VOV			-0.175	-0.166			-0.134	-0.155	-0.165	-0.154
			(-8.07)	(-7.37)			(-5.68)	(-6.86)	(-7.34)	(-6.97)
$Adj.R^2$	0.3%	0.4%	3.3%	3.4%	0.7%	1.0%	3.4%	3.5%	3.2%	3.6%
$Avg.\#firms$	1537	1502	1463	1401	1549	1427	1417	1401	1416	1401

Table 6: Investment Performance Evaluation

This table evaluates the investment performance of various option strategies. In addition to the cross-sectional long-short strategies sorted by various option predictors from PM1 to VOV, we include two time-series strategies that short an equal-weighted portfolio of cross-sectional straddles and short the SPX index straddle. In those cross-sectional strategies, we use equal-weighted long-short return spread from quintile sort and rebalance the portfolio every month. All performance metrics are applied to the strategy returns at monthly frequency. To facilitate comparison, we adjust the sign of each strategy such that its average return is positive. T-statistics in parentheses are Newey-West adjusted with 3 lags.

	Mean return	T-stats	StdDev	Sharpe ratio	Skewness	Excess kurtosis	Max drawdown
PM1	2.96%	(7.69)	6.30%	0.47	0.97	3.36	21.21%
PM3	4.10%	(10.09)	6.21%	0.66	0.56	1.31	27.83%
PM12	5.67%	(14.68)	6.53%	0.87	0.62	1.11	13.61%
PM24	5.70%	(13.72)	6.67%	0.85	0.34	1.11	19.75%
MOM1	3.76%	(9.21)	5.19%	0.72	0.52	1.08	29.91%
MOM3	5.36%	(13.38)	5.16%	1.04	0.39	0.37	10.06%
MOM12	6.58%	(16.24)	5.65%	1.16	-0.47	4.17	29.10%
MOM24	6.05%	(15.34)	5.50%	1.10	0.00	-0.04	15.28%
Market cap.	4.70%	(7.21)	9.99%	0.47	1.32	5.21	52.42%
Idiosyncratic vol.	3.14%	(5.51)	9.05%	0.35	2.89	26.71	76.79%
IV term spread	5.49%	(13.53)	6.16%	0.89	1.65	14.04	24.09%
IV smirk	0.39%	(1.37)	4.25%	0.09	0.48	1.67	75.72%
IV-HV	10.89%	(17.56)	7.91%	1.38	0.43	1.00	17.70%
VOV	4.61%	(10.17)	6.19%	0.74	0.43	0.54	31.08%
Short EW straddle	4.88%	(6.96)	11.94%	0.41	-3.62	29.96	$> 100\%$
Short SPX straddle	5.90%	(3.69)	27.52%	0.21	-1.65	7.11	$> 100\%$

Table 7: Alternative Straddle Returns

This table examines three methods for computing straddle returns: In addition to the daily-delta-hedged straddle return used in the main analysis, which we call 'dynamic straddle', we consider the 'static straddle' return, which is the return on a static position of monthly held-to-maturity straddle without any delta-hedge, and the 'bias-corrected dynamic straddle' return, which performs the daily delta hedging with deltas that are lagged one extra day. Panel A reports the average high-minus-low return spread (in percentage) of quintile sorts under each method. T-statistics in parentheses are Newey-West adjusted with 3 lags. In the quintile sort, both peer momentum signal and one-month-ahead return use the same type of straddle return under each method. Panel B reports time-series average of the cross-sectional correlations between each straddle return and the return on a synthetic variance swap, defined as realized daily variance divided by implied variance minus one.

Panel A: Peer momentum strategy returns

	Dynamic straddle	Static straddle	Bias-corrected dynamic straddle
PM1	2.96	0.30	2.68
	(7.69)	(0.29)	(5.74)
PM3	4.10	0.56	4.42
	(10.09)	(0.67)	(8.99)
PM12	5.67	4.27	6.15
	(14.68)	(5.45)	(13.51)
PM24	5.70	3.95	5.86
	(13.72)	(4.89)	(12.41)

Panel B: Correlation with variance swap return

	Correlation(#, variance swap return)		
	Dynamic straddle	Static straddle	Bias-corrected dynamic straddle
Mean	0.771	0.419	0.661

Table 8: Adjusting for Transactions Costs

This table reports the average returns of analyst-based PM strategies after adjusting for option bid-ask spreads. We report results for the baseline strategies based on quintile sorts, as well as transaction-cost-reducing strategies that use extreme deciles or a low-cost sample consisting exclusively of straddles whose percentage bid-ask spreads fall into the lowest quartile each month after the portfolio sort. We consider sizes of transaction costs ranging from zero to the full quoted half-spread. Intermediate cases include the algo, adjusted, and effective spreads, which are 20.3%, 51.6%, and 75.8%, respectively, as large as the quoted spreads (Muravyev and Pearson, 2020). All returns are monthly and in percentages. T-statistics in parentheses are Newey-West adjusted with 3 lags.

Panel A: Strategy based on PM1					
	None	Algo	Adjusted	Effective	Quoted
Main sample with quintiles	2.96	-1.35	-8.37	-14.50	-22.90
	(7.69)	(-3.42)	(-15.49)	(-18.44)	(-16.55)
Main sample with deciles	3.88	-0.59	-7.92	-14.40	-23.58
	(7.60)	(-1.17)	(-12.51)	(-16.11)	(-14.92)
Low-cost sample with deciles	2.07	0.88	-0.94	-2.36	-3.77
	(2.99)	(1.29)	(-1.39)	(-3.49)	(-5.59)
Panel B: Strategy based on PM12					
	None	Algo	Adjusted	Effective	Quoted
Main sample with quintiles	5.67	1.28	-6.02	-12.55	-21.74
	(14.68)	(3.29)	(-10.97)	(-14.96)	(-14.23)
Main sample with deciles	7.51	2.89	-4.86	-11.92	-22.06
	(14.77)	(5.92)	(-7.69)	(-12.49)	(-12.65)
Low-cost sample with deciles	6.97	5.81	4.01	2.62	1.22
	(8.76)	(7.30)	(5.03)	(3.27)	(1.52)

Table 9: Peer Momentum and Attention

This table reports mean returns and t-statistics from sequential double sorts on straddles. In Panel A, on the third Friday of each month, focal firms' straddles are first sorted into two halves based on the conditioning variable in the column header. Within each half, straddles are further sorted into quintile portfolios based on peer momentum signal. The reported values are the equal-weighted high-minus-low return spreads within each conditioning subsample. In Panel B, each focal firm's peers are first sorted into two halves based on the conditioning variable, and peer momentum is constructed separately from each half of peers. We then sort focal firms' straddles into quintiles based on these peer momentum measures and report the equal-weighted high-minus-low return spreads. The conditioning variables are defined as follows: Analyst coverage is the total number of analysts covering the focal (Panel A) or peer (Panel B) stock; Firm size is the stock's most recent equity capitalization; Option volume is the most recent month's option trading volume scaled by average monthly option trading volume over the prior 12 months for the focal (Panel A) or peer (Panel B) firm; Google search is the Search Volume Index from Google Trends; and EDGAR views is the total human downloads of a firm's 10-K, 10-Q, and 8-K filings during the most recent month. All returns are monthly and in percentages. T-statistics in parentheses are Newey-West adjusted with 3 lags.

	Analyst coverage	Firm size	Option volume	Google search	EDGAR view	Analyst coverage	Firm size	Option volume	Google search	EDGAR view
	1-month formation period					12-month formation period				
Panel A: Focal firm subsamples										
Low	3.23	3.27	2.83	3.68	3.21	5.61	5.86	5.05	6.82	5.78
	(8.37)	(8.07)	(7.76)	(6.81)	(5.08)	(14.17)	(14.16)	(11.98)	(12.94)	(10.36)
High	2.35	2.10	3.01	1.84	1.50	4.48	4.20	5.86	3.95	3.88
	(5.32)	(5.18)	(6.46)	(3.74)	(2.55)	(9.60)	(9.25)	(14.22)	(8.86)	(5.98)
High-Low	-0.88	-1.16	0.18	-1.84	-1.70	-1.12	-1.65	0.81	-2.86	-1.90
	(-2.27)	(-2.79)	(0.48)	(-3.92)	(-2.82)	(-2.46)	(-3.19)	(2.40)	(-6.32)	(-3.02)
Panel B: Peer firm subsamples										
Low	2.71	2.71	2.94	2.92	2.81	4.62	4.61	4.90	5.53	4.30
	(7.90)	(7.94)	(7.71)	(7.18)	(5.21)	(13.00)	(13.56)	(14.10)	(12.40)	(9.05)
High	2.36	2.34	2.17	1.94	1.46	4.50	4.45	4.65	4.28	3.45
	(6.69)	(6.67)	(6.68)	(4.42)	(3.52)	(11.72)	(11.53)	(12.41)	(10.67)	(7.39)
High-Low	-0.34	-0.37	-0.76	-0.97	-1.35	-0.12	-0.16	-0.25	-1.25	-0.85
	(-1.45)	(-1.53)	(-2.79)	(-3.72)	(-3.16)	(-0.46)	(-0.66)	(-1.07)	(-4.50)	(-2.41)

Table 10: Peer Momentum Based on Alternative Linkages

This table compares our benchmark analyst-based PM signal to PM signals based on alternative linkages specified in the rows. Panel A examines PM signals constructed over 1-month formation period, while Panel B uses 12-month formation period. In each panel, the left-most columns report univariate Fama-MacBeth regressions in which we predict straddle returns using a single PM signal. The middle columns present bivariate regressions that include both the analyst-based PM signal and an alternative PM signal. The right-most columns include the additional control variables from Table 5. T-statistics in parentheses are Newey-West adjusted with 3 lags.

Panel A: 1-month formation period

	Univariate regressions			Bivariate regressions			Multivariate regression with controls		
Alternative PM	Analyst	Alt.	Adj.R^2	Analyst	Alt.	Adj.R^2	Analyst	Alt.	Adj.R^2
	0.111		0.4%						
	(8.09)								
Complicated Firms		0.037	0.1%	0.084	0.017	0.4%	0.082	0.025	3.9%
		(3.08)		(4.72)	(1.61)		(4.97)	(2.16)	
Customer		0.005	0.1%	0.120	-0.002	0.5%	0.097	-0.001	3.9%
		(1.12)		(5.96)	(-0.32)		(4.80)	(-0.23)	
Customer Industry		-0.003	0.2%	0.120	-0.018	0.6%	0.098	0.001	3.5%
		(-0.20)		(8.32)	(-1.08)		(7.47)	(0.08)	
Geography		0.016	0.0%	0.107	0.007	0.4%	0.089	0.003	3.3%
		(2.21)		(7.66)	(0.91)		(7.02)	(0.36)	
Light GBM		0.770	0.6%	0.077	0.704	0.8%	0.083	0.396	3.4%
		(11.86)		(6.28)	(11.40)		(6.80)	(9.01)	
K-means		0.239	0.4%	0.078	0.204	0.6%	0.072	0.159	3.5%
		(10.74)		(6.13)	(9.91)		(5.92)	(9.49)	
Supplier Industry		0.106	0.2%	0.117	0.077	0.6%	0.095	0.069	3.6%
		(4.04)		(8.14)	(2.95)		(7.29)	(2.64)	
Technology		0.202	0.3%	0.091	0.150	0.6%	0.070	0.105	3.7%
		(7.44)		(5.62)	(6.18)		(4.60)	(4.43)	
TNIC3		0.037	0.2%	0.102	0.011	0.4%	0.082	0.013	3.4%
		(6.68)		(7.29)	(2.45)		(6.51)	(3.06)	
Composite		0.495	0.7%	-0.022	0.525	0.8%	0.012	0.341	3.5%
		(11.89)		(-1.88)	(11.89)		(0.97)	(9.53)	

Table 10: Continued

Panel B: 12-month formation period

	Univariate regressions			Bivariate regressions			Multivariate regression with controls		
Alternative PM	Analyst	Alt.	Adj.R^2	Analyst	Alt.	Adj.R^2	Analyst	Alt.	Adj.R^2
	0.545		0.7%						
	(17.26)								
Complicated Firms		0.134	0.3%	0.424	0.025	0.8%	0.264	0.051	4.0%
		(3.58)		(9.60)	(0.69)		(5.53)	(1.44)	
Customer		0.036	0.1%	0.596	-0.015	1.0%	0.392	-0.027	4.1%
		(2.45)		(12.18)	(-0.99)		(6.93)	(-1.62)	
Customer Industry		-0.011	0.2%	0.593	-0.029	1.0%	0.363	0.033	3.6%
		(-0.23)		(17.60)	(-0.70)		(10.67)	(0.83)	
Geography		0.127	0.0%	0.546	0.047	0.7%	0.342	0.028	3.3%
		(6.19)		(17.13)	(2.47)		(10.50)	(1.46)	
Light GBM		1.318	0.8%	0.086	1.247	1.0%	0.093	0.154	3.4%
		(11.89)		(6.62)	(11.53)		(7.29)	(1.74)	
K-means		0.566	0.6%	0.435	0.349	1.0%	0.288	0.240	3.5%
		(12.27)		(15.33)	(8.16)		(9.45)	(5.44)	
Supplier Industry		0.345	0.2%	0.590	0.104	1.0%	0.361	0.128	3.7%
		(5.34)		(16.97)	(1.68)		(10.92)	(2.15)	
Technology		0.781	0.6%	0.551	0.365	1.1%	0.327	0.233	3.8%
		(12.52)		(14.87)	(6.61)		(9.02)	(4.22)	
TNIC3		0.252	0.4%	0.491	0.086	0.8%	0.291	0.062	3.4%
		(16.24)		(14.49)	(7.45)		(8.76)	(5.29)	
Composite		1.178	1.0%	0.230	0.862	1.1%	0.253	0.258	3.5%
		(15.89)		(7.08)	(9.99)		(8.49)	(3.25)	

Table 11: Variance Prediction

This table reports the results of Fama-MacBeth regressions in which the dependent variable is the log of the realized variance over the straddle holding period from month $t-1$ to month t ($Ln(RV_t)$), the log of the at-the-money straddle implied variance at the straddle formation date of month $t-1$ ($Ln(IV_{t-1})$), or the log variance swap return ($Ln(RV_t/IV_{t-1})$). Independent variables, including peer momentum and momentum signals, are measured at the straddle formation date in month $t-1$ using past straddle returns. T-statistics in parentheses are Newey-West adjusted with 3 lags. Panels A and B differ with respect to the formation period used in the peer momentum and momentum signals.

Panel A: 1-month formation period

	$Ln(RV_t)$ (1)	$Ln(RV_t)$ (2)	$Ln(RV_t)$ (3)	$Ln(IV_{t-1})$ (4)	$Ln(RV_t/IV_{t-1})$ (5)
PM1	0.620	0.601	0.336	0.256	0.345
	(4.73)	(4.76)	(10.39)	(2.12)	(10.62)
MOM1		0.043	0.026	0.017	0.026
		(3.33)	(3.88)	(1.55)	(3.78)
$Ln(IV_{t-1})$			0.906		
			(140.41)		
$Adj.R^2$	2.8%	3.1%	60.2%	3.7%	1.0%
$Avg.\#firms$	1537	1502	1502	1502	1502

Panel B: 12-month formation period

	$Ln(RV_t)$ (1)	$Ln(RV_t)$ (2)	$Ln(RV_t)$ (3)	$Ln(IV_{t-1})$ (4)	$Ln(RV_t/IV_{t-1})$ (5)
PM12	2.136	1.783	1.402	0.402	1.381
	(3.92)	(3.48)	(17.15)	(0.78)	(21.10)
MOM12		0.752	0.430	0.353	0.400
		(15.31)	(20.17)	(6.23)	(16.97)
$Ln(IV_{t-1})$			0.901		
			(146.04)		
$Adj.R^2$	4.7%	5.7%	59.8%	6.3%	2.3%
$Avg.\#firms$	1549	1427	1427	1427	1427

Table 12: Peer Momentum and Factor Momentum Based on IPCA

This table examines the relation between peer momentum and factor momentum through decomposing focal and peer firms' straddle returns into systematic (IPCA-explained) and residual components. In Panel A, focal firms' straddles are sorted into quintiles based on peer momentum calculated over various formation periods. The left (right) columns sort on the systematic (residual) component of peer momentum. The table reports the high-minus-low return spreads (in percentages) across focal firms' total returns as well as their systematic and residual components. Panel B presents Fama-MacBeth regressions where the dependent variables are focal firms' total straddle returns or their systematic and residual components. Control variables are the same as those in Table 5. The underlying IPCA specification uses a 3-factor model without an intercept. The instruments utilized include the 46 characteristics from Goyal and Saretto (2025) and a constant. These 46 characteristics are cross-sectionally rank standardized. When implementing IPCA, we consider straddle returns for all straddles, regardless of whether they have positive open interest or not. T-statistics in parentheses are Newey-West adjusted with 3 lags. The sample period covers January 1996 to November 2024.

Panel A: High-minus-low return spread from quintile sort

Formation period	Sorted by systematic peer momentum			Sorted by residual peer momentum			Avg. # firms
	Focal total	Focal systematic	Focal residual	Focal total	Focal systematic	Focal residual	
1	3.90	3.18	0.72	1.72	-0.28	2.01	1535
	(8.75)	(10.85)	(2.11)	(4.65)	(-2.43)	(5.42)	
3	4.17	3.88	0.30	2.84	-0.31	3.15	1537
	(10.47)	(18.36)	(0.88)	(7.34)	(-2.11)	(8.54)	
12	4.49	3.89	0.59	4.17	0.85	3.32	1549
	(10.04)	(18.31)	(1.57)	(11.18)	(5.06)	(9.50)	
24	4.73	3.93	0.80	4.08	1.17	2.91	1537
	(10.56)	(18.10)	(2.14)	(10.74)	(6.60)	(8.27)	

Panel B: Fama-MacBeth regressions

Formation period	Total returns as dep. var.			Systematic returns as dep. var.			Residual returns as dep. var.			Avg. # firms
	Systematic PM	Residual PM	Adj.R^2	Systematic PM	Residual PM	Adj.R^2	Systematic PM	Residual PM	Adj.R^2	
1	0.338	0.082	3.6%	0.254	0.006	55.3%	0.083	0.076	1.6%	1417
	(4.77)	(6.34)		(9.90)	(2.86)		(1.24)	(6.04)		
3	0.404	0.170	3.6%	0.359	0.014	55.3%	0.045	0.156	1.6%	1417
	(5.75)	(7.52)		(15.55)	(3.21)		(0.68)	(7.36)		
12	0.500	0.289	3.6%	0.426	0.019	55.2%	0.073	0.269	1.7%	1417
	(5.41)	(8.13)		(16.29)	(1.85)		(0.85)	(7.98)		
24	0.561	0.309	3.6%	0.466	0.019	55.0%	0.094	0.289	1.6%	1417
	(6.03)	(6.56)		(18.38)	(1.44)		(1.11)	(6.60)		

Table 13: Peer Momentum and Factor Momentum Based on Käfer, Mörke, and Wiest (2026)

This table reports spanning tests between peer momentum, own momentum, and cross-sectional factor (CSF) momentum. Panel A regress peer momentum or own momentum factor on CSF momentum, while Panel B reports the reverse regressions of CSF momentum on peer momentum or own momentum factor. Peer momentum and own momentum factor are constructed as in Table 3. Following Käfer, Mörke, and Wiest (2026), CSF momentum is constructed using 28 firm characteristics. For each characteristic, stocks are sorted monthly into deciles to form characteristic-based long-short portfolios. The sorting direction for each characteristic portfolio is determined using an expanding window with a burn-in period from 1996 to 1998. The sample period covers January 1999 to November 2024. T-statistics in parentheses are Newey-West adjusted with 3 lags.

Panel A: Peer momentum or own momentum regressed on CSF momentum

Formation period	Peer Momentum as dep. var.			Own Momentum as dep. var.		
	Alpha	CSF Momentum	R^2	Alpha	CSF Momentum	R^2
1	0.0060	0.6467	32.1%	0.0194	0.4098	19.8%
	(1.78)	(8.92)		(4.78)	(4.64)	
3	0.0136	0.6083	22.2%	0.0300	0.4506	18.4%
	(2.71)	(6.20)		(6.63)	(4.29)	
12	0.0238	0.6962	22.0%	0.0377	0.4808	14.9%
	(4.58)	(7.13)		(7.15)	(3.93)	
24	0.0336	0.4924	12.7%	0.0408	0.2677	6.1%
	(4.81)	(3.99)		(4.98)	(1.45)	

Panel B: CSF momentum regressed on peer momentum or own momentum

Formation period	CSF Momentum as dep. var.			CSF Momentum as dep. var.		
	Alpha	Peer Momentum	R^2	Alpha	Own Momentum	R^2
1	0.0214	0.4962	32.1%	0.0194	0.4830	19.8%
	(6.85)	(5.45)		(6.07)	(7.62)	
3	0.0298	0.3649	22.2%	0.0242	0.4079	18.4%
	(10.06)	(7.34)		(5.15)	(5.54)	
12	0.0298	0.3159	22.0%	0.0291	0.3099	14.9%
	(9.81)	(8.05)		(3.98)	(2.96)	
24	0.0304	0.2569	12.7%	0.0327	0.2265	6.1%
	(10.73)	(5.30)		(4.41)	(2.10)	

Table 14: Decomposing Analyst Peer Momentum Strategy: Asymmetry vs. Symmetry

This table decomposes the returns of analyst-based peer momentum strategy into its asymmetric and symmetric components. We first construct the prediction matrix Π of analyst-based peer option momentum strategy, where $\Pi_{i,j} = \frac{n_{i,j}}{\sum_{j \neq i} n_{i,j}}$ for $i \neq j$, and $\Pi_{i,i} = 0$, with $n_{i,j}$ as the common analyst number between focal firm i and peer firm j. The overall monthly strategy return (All) is then calculated as $S'LR$, where S is the vector of raw option momentum signal, $L = \Pi'$ is the position matrix that translates signals into portfolio weights, and R is the vector of cross-sectionally demeaned, one-month-ahead straddle returns. This 'All' return is further decomposed into asymmetric ($S'\,\mathrm{ASY}\,R$) and symmetric ($S'\,\mathrm{SYM}\,R$) components, where $ASY = (L - L')/2$ and $SYM = (L + L')/2$. To facilitate comparison, strategy returns are scaled such that the volatility of 'All' matches that of an equal-weighted straddle portfolio, and their monthly averages are reported in percentages. T-statistics in parentheses are Newey-West adjusted with 3 lags. The last row reports the correlation between the matrix-based strategy return 'All' and our baseline sort-based strategy return from Table 3.

	1-month formation period	12-month formation period
All	3.98	8.80
	(5.30)	(11.57)
Asymmetry	0.86	1.80
	(3.76)	(4.87)
Symmetry	3.13	7.00
	(3.79)	(9.04)
Asymmetry/All	22%	20%
Correlation with baseline sort-based strategy	0.828	0.896

Table 15: Data-Driven Strategies

This table compares three option peer strategies: 'Analyst' (the baseline analyst-based peer momentum strategy from Table 14, re-evaluated over the same shorter sample period as the data-driven strategies), 'DD' (a data-driven strategy exploiting historical cross-firm lead-lag relationships), and 'DDAW' (a hybrid strategy that modulates the baseline analyst strategy using historical cross-firm lead-lag relationships). Strategy return (All) are calculated as $S'LR$, where S is the vector of raw option momentum signal, L is the position matrix that translates signals into portfolio weights, and R is the vector of cross-sectionally demeaned, one-month-ahead straddle returns. Details about constructing the position matrix L for 'DD' and 'DDAW' strategies are described in Section 5. For 'DD' and 'DDAW', we also report two sub-strategies exploiting cross-momentum ($L > 0$) and cross-reversal ($L < 0$) relationships, respectively. The strategy returns are scaled such that the volatility of 'All' matches that of an equal-weighted straddle portfolio, and their monthly averages are reported in percentages. T-statistics in parentheses are Newey-West adjusted with 3 lags. The sample period covers 2001 to 2024.

	Analyst	DD			DDAW		
	All	All	L> 0	L< 0	All	L> 0	L< 0
Panel A: 1-month formation period							
Mean return	4.00	5.20	1.62	3.58	2.77	4.14	-1.37
	(4.58)	(6.57)	(3.33)	(6.54)	(3.73)	(2.97)	(-1.18)
Sharpe ratio	1.11	1.44	0.45	0.99	0.77	1.15	-0.38
Avg.#firms	1568	1568	1568	1568	1568	1568	1568
Avg.#peers	69	1115	549	566	56	28	28
Panel B: 12-month formation period							
Mean return	9.16	8.90	5.30	3.60	9.36	7.27	2.09
	(10.54)	(8.66)	(8.79)	(7.96)	(9.94)	(9.89)	(3.41)
Sharpe ratio	2.54	2.47	1.47	1.00	2.60	2.02	0.58
Avg.#firms	1481	1481	1481	1481	1481	1481	1481
Avg.#peers	69	1108	554	555	57	28	29

Table 16: Return Spanning between Analyst and Data-Driven Strategies

This table reports the results of spanning tests between the baseline analyst-based peer momentum strategy from Table 14 and the two data-driven strategies (DD and DDAW) from Table 15. For both DD and DDAW, All L represents the strategy itself while L>0 refers to the sub-strategy that exploits only cross-momentum. T-statistics in parentheses are Newey-West adjusted with 3 lags. The sample period covers 2001 to 2024.

Panel A: 1-month formation period

	DD				DDAW			
Dep. var.	Alpha	All L	L> 0	R^2	Alpha	All L	L> 0	R^2
Analyst	0.0400				0.0400			
	(4.58)				(4.58)			
	0.0346	0.1051		1%	0.0272	0.4641		19%
	(4.32)	(1.27)			(4.44)	(4.18)		
	0.0378		0.1411	1%	0.0171		0.5532	82%
	(4.61)		(0.88)		(5.70)		(16.17)	
	Alpha	Analyst		R^2	Alpha	Analyst		R^2
All L	0.0520				0.0277			
	(6.57)				(3.73)			
	0.0483	0.0926		1%	0.0113	0.4089		19%
	(5.99)	(1.37)			(1.79)	(7.41)		
	Alpha	Analyst		R^2	Alpha	Analyst		R^2
L> 0	0.0162				0.0414			
	(3.33)				(2.97)			
	0.0143	0.0487		1%	-0.0176	1.4734		82%
	(3.09)	(1.04)			(-3.53)	(14.00)		

Panel B: 12-month formation period

	DD				DDAW			
Dep. var.	Alpha	All L	L> 0	R^2	Alpha	All L	L> 0	R^2
Analyst	0.0916				0.0916			
	(10.54)				(10.54)			
	0.0456	0.5170		24%	0.0329	0.6268		35%
	(3.83)	(5.27)			(3.24)	(7.37)		
	0.0466		0.8487	20%	0.0183		1.0081	71%
	(4.12)		(5.38)		(3.09)		(18.13)	
	Alpha	Analyst		R^2	Alpha	Analyst		R^2
All L	0.0890				0.0936			
	(8.66)				(9.94)			
	0.0471	0.4575		24%	0.0428	0.5546		35%
	(7.85)	(6.28)			(5.82)	(10.19)		
	Alpha	Analyst		R^2	Alpha	Analyst		R^2
L> 0	0.0530				0.0727			
	(8.79)				(9.89)			
	0.0311	0.2396		20%	0.0078	0.7091		71%
	(8.13)	(5.77)			(1.89)	(20.24)		

Table 17: Peer Reversal

This table reports mean returns and t-statistics from univaraiate quintile sorts based on peer reversal signals. On the third Friday of each month, we identify reversal peers for each focal firm using the negative entries in the position matrix L from the DD or DDAW strategy. Under the DD approach, reversal peers are firms whose historical returns are negatively related to the focal firm's future returns. Under the DDAW approach, reversal peers are firms that share common analysts with the focal firm and whose historical returns are negatively related to the focal firm's future returns. We then form peer reversal signals by calculating a weighted sum of past returns of the reversal peers for each focal firm. When reversal peers are identified using the DD approach, we weight them by the absolute value of the position matrix L estimate linking each peer to a given focal firm. When they are identified using the DDAW approach, we weight them by the reciprocal of the number of shared analysts. We then sort focal firms' straddles into quintiles based on their peer reversal signals and report the mean returns (in percentages) for each portfolio. T-statistics in parentheses are Newey-West adjusted with 3 lags. The sample period covers 2001 to 2024.

Panel A: Sorts based on DD signals						
Formation period	Low	2	3	4	High	High-Low
1	-3.74	-3.82	-4.43	-4.80	-6.13	-2.38
	(-4.21)	(-4.56)	(-5.30)	(-5.72)	(-7.59)	(-7.94)
12	-2.80	-3.12	-4.04	-5.17	-7.74	-4.94
	(-3.41)	(-3.62)	(-4.70)	(-6.00)	(-9.29)	(-14.02)
Panel B: Sorts based on DDAW signals						
Formation period	Low	2	3	4	High	High-Low
1	-5.72	-4.58	-3.96	-3.85	-4.47	1.25
	(-7.55)	(-5.55)	(-4.58)	(-4.40)	(-4.96)	(4.06)
12	-5.12	-3.63	-3.93	-4.10	-5.65	-0.53
	(-6.39)	(-4.26)	(-4.63)	(-4.64)	(-6.62)	(-1.71)

Appendix

Table A1: Peer Option Momentum with Different Lags

This table reports the results of Fama-MacBeth regressions in which straddle return is regressed on the peer option momentum signals constructed with different past windows. Here, we choose nonoverlapping past windows to avoid information overlapping in different peer momentum signals. Panel A (Panel B) shows the regression results without (with) control variables. When specified, the control variables include option momentum signals measured over the same past windows as the peer momentum signals, log of stock market capitalization, idiosyncratic volatility, IV term spread, IV smirk, IV-HV, and VOV. T-statistics in parentheses are Newey-West adjusted with 3 lags.

Panel A: Without controls						
	(1)	(2)	(3)	(4)	(5)	(6)
PM1	0.111	0.070	0.059	0.058	0.048	0.046
	(8.08)	(5.39)	(4.70)	(4.51)	(3.68)	(3.57)
PM2to12		0.463	0.387	0.371	0.360	0.350
		(15.03)	(12.13)	(11.43)	(9.65)	(9.33)
PM13to24			0.181	0.131	0.106	0.078
			(4.64)	(3.23)	(2.65)	(1.99)
PM25to36				0.146	0.090	0.105
				(4.37)	(2.50)	(2.90)
PM37to48					0.148	0.115
					(3.76)	(2.75)
PM49to60						0.097
						(2.67)
Control	No	No	No	No	No	No
$Adj.R^2$	0.3%	0.9%	1.2%	1.4%	1.6%	1.8%
$Avg.\#firms$	1537	1551	1562	1566	1569	1571
Panel B: With controls						
	(1)	(2)	(3)	(4)	(5)	(6)
PM1	0.093	0.068	0.058	0.055	0.044	0.037
	(7.73)	(5.58)	(4.60)	(4.13)	(2.91)	(2.40)
PM2to12		0.274	0.239	0.240	0.240	0.234
		(8.78)	(7.26)	(7.14)	(6.28)	(6.18)
PM13to24			0.052	0.044	0.017	-0.023
			(1.38)	(1.07)	(0.39)	(-0.55)
PM25to36				0.017	-0.009	0.006
				(0.44)	(-0.21)	(0.14)
PM37to48					0.074	0.029
					(1.86)	(0.70)
PM49to60						0.076
						(1.71)
Control	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	3.3%	3.7%	3.9%	4.1%	4.4%	4.6%
$Avg.\#firms$	1463	1386	1265	1151	1056	978