Diversification in Lottery-Like Features and Portfolio Pricing Discounts*

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Abstract

Why is a portfolio sometimes valued less than the sum of its underlying components? In this paper, I provide a novel explanation for this question by utilizing closed-end funds, mergers and acquisitions, and conglomerates, where the value of the aggregate portfolio and the values of the underlying components can be separately evaluated. Inspired by the model of Barberis and Huang (2008), in which lottery-like stocks are overvalued due to probability weighting, I argue that a portfolio holding lottery-like stocks should be valued less than the total value of its components, because lottery-like features get diversified away when lottery-like stocks do not hit "jackpots" together. I present evidence supporting this argument and provide a novel and unifying explanation for the closed-end fund discount puzzle, the announcement-day returns of mergers and acquisitions, and the conglomerate discount.

Keywords: Lottery-like feature, Co-maxing out, Portfolio Discounts

JEL Classification: G02, G11, G12, G20

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1. Introduction

In financial markets, a portfolio is sometimes valued less than the sum of its underlying components, which is puzzling. For example, closed-end fund shares typically sell at prices lower than the per share market value of assets the fund holds; mergers and acquisition deals often have negative combined announcement-day returns; the average conglomerate is worth less than a portfolio of comparable single-segment firms. In this paper, I provide a novel answer for the puzzle and a unified explanation for these three seemingly unrelated phenomena, based on the diversification of lottery-like features, which is inspired by the theoretical work of Barberis and Huang (2008).

Under the framework of Tversky and Kahneman's (1992) cumulative prospect theory with a particular focus on its probability weighting, Barberis and Huang (2008) show that, a lottery-like (i.e., positively skewed) stock can become overpriced relative to the prediction from the traditional expected utility model. Inspired by this model implication, I argue that a portfolio holding lottery-like stocks should be valued less than the total value of its components, because these lottery-like stocks do not simultaneously hit "jackpots" and the lottery-like features are diversified away in the portfolio. Thus, the portfolio cannot provide a similar lottery-like payoff as the payoffs from the lottery-like holdings. Since lottery-like assets are traded at a price premium while non-lottery-like assets are not, the portfolio should be traded at a discount relative to its underlying assets due to the discrepancy in the level of lottery likeness between the portfolio and its holdings.

To illustrate, consider a simplified example with two lottery-like stocks (denoted A & B) and a portfolio holding half of Stock A and half of Stock B. There are three identical investors following cumulative prospective theory described in Barberis and Huang (2008), each trading one asset respectively due to market segmentation.[1] Both stocks follow a same binomial distribution: with a low probability p, the security pays out a large "jackpot", and with probability $1-p$, it pays out nothing. The model implies that both A & B are traded at a premium due to their lottery-like payoffs. However, the price of the portfolio depends on how

[1] Such segmentation may be the result of, say, limited attentions, budget constraints, transaction costs, participation costs, etc.

likely A & B hit "jackpots" together. First, assume A & B are identical, i.e., they always hit "jackpots" together. This means that the payoff distribution of the portfolio is the same as the two lottery-like stocks. Therefore, three assets are equally priced. In the second case, assume A & B always hit "jackpots" in different times. This means that the lottery-like features are diversified away in the portfolio, and the payoff distribution for the portfolio is no longer lottery-like. According to Barberis and Huang (2008), the portfolio should be priced as predicted by the expected utility theory while A & B are traded at a price premium. Therefore, the portfolio is traded at a discount relative to the total value of its components.

Since stocks are combined and traded "as a package", the difference in per share price between a portfolio and its holdings should not be affected by firm fundamentals that are well-documented to have asset pricing powers but can be potentially correlated with lottery-like features. However, I document that a portfolio's holdings exhibit stronger lottery-like features relative to the portfolio itself. Utilizing this unique feature, I provide evidence supporting Barberis and Huang (2008), showing that the relative lottery-likeness of a portfolio's holdings help explains the portfolio discount.

My novel channel draws on an interaction effect between lottery-like features and the tendency of hitting "jackpots" together. If stocks A & B do not offer lottery-like payoffs in the first place, they are not overpriced individually, and the idea of "hitting jackpots together" is of little practical consequence. On the other hand, if stocks A & B always hit "jackpots" together, there should be no discrepancy between the portfolio and the sum of its components even if both stocks have strong lottery-like features.

The first setting I exploit is US equity closed-end funds (CEFs). A CEF is a type of mutual fund which typically holds other publicly traded securities. Unlike an open-end fund, a CEF issues a fixed number of shares which are not redeemable from the fund. The CEF setting draws the closest parallel to the aforementioned example. The key variable of interests is the CEF discount, defined as the difference between the price per share of the CEF and the price per share of its net asset value (NAV), divided by NAV. This variable reflects the difference between the value of a portfolio (price per share of the CEF) and the total value of its components (price per share of the NAV). Based on the illustration, the CEF should be traded at a discount, if the lottery-like feature of its holdings is stronger than the lottery-like feature of the CEF itself. However, this discount should be mitigated if the tendency of lottery-like holdings hitting "jackpots" together is high as well.

For the CEF analyses, I only consider a fund's top-ten holdings, because I conjecture that when investors gauge their level of excitement about a portfolio, they focus on the portfolio's top-ten holdings, which are readily observable on the fund's website, the fund's factsheet and financial medias such as Morningstar and Yahoo! Finance. The entire holding position, however, may not be available to the investors. The other reason is to reduce computation when I measure hitting "jackpots" together for each stock pair, as described latter. The average CEF in our sample holds around 100 stocks. Focusing on the top ten helps reduce the calculation to a manageable level. Having said that, my results are robust to including stocks outside of a fund's top ten.

Motivated by existing literature, I follow Bali, Cakici, and Whitelaw (2011) and proxy the lottery-like feature for each stock via the average top five daily returns within a month (Max5). The idea is that it captures the low probability and extreme return states that drive the results in the model of Barberis and Huang (2008). To assess the discrepancy between the lottery-like feature of the fund and the lottery-like feature of its top-ten holdings, I define Ex_Max5 as the difference between CEF's Max5 (CEF_Max5) and its top-ten holdings' average Max5 (Holding_Max5). To produce a measure for the tendency of hitting "jackpots" together, I check the percentage of top five daily returns happen at the same time (CoMax5) for every possible pair of stocks within a CEF's top-ten holdings. The lottery-like feature of the stock pair is proxied by the portfolio-weighted average Max5 from both stocks (Pair_Max5). The interaction of Pair_Max5 and CoMax5 provides useful information about both the level of the lottery-likeness and the tendency of hitting "jackpots" together. All pair-level variables are further integrated into the fund level, as outlined in Section 3.1.

Based on my illustration, a regression of CEF discount on Ex_Max5 and various control variables should produce a strong positive slope on Ex_Max5, i.e., if the lottery-like feature of a CEF's holding is relatively stronger than the lottery-like feature of the CEF, the CEF is traded at a bigger discount. Consistent with this prediction, the estimate on Ex_Max5 is 0.990

(t-statistic = 2.81), which suggests that a one-standard deviation increase in the relative lottery-likeness of a CEF's holdings comes with 0.990% increase in the CEF discount. For reference, the average CEF discount in my sample is 4.7%. I further examine the effect of the interaction of Pair_Max5 and CoMax5. I find that the coefficient for this interaction is significantly positive, suggesting that the discount can be partially mitigated if lottery-like holdings tend to hit "jackpots" together. A one-standard deviation increase in the interaction term comes with 0.520% (t-statistic = 2.92) drop on the CEF discount. Both results survive the inclusion of various variables known to be associated with CEF discounts.

This idea can also help explain the market reactions to mergers and acquisitions (M&A). In this setting, the discrepancy between the value of the portfolio (i.e., the value of the joint firm) and the total value of its components (i.e., the value of the acquirer plus the value of the target) is reflected by the combined announcement-day return (denoted as Combined_CAR[−1,+1]). The lottery-like feature of the deal should negatively predict Combined_CAR[−1,+1]. However, if the acquirer and the target exhibit strong lottery-like features and they tend to hit "jackpots" together, the effect should be partially mitigated.

I conjecture that investors generally take a longer horizon to evaluate M&A deals, therefore, the lottery-like feature of the acquirer (target) is proxied by the average of the acquirer's (target's) top-three monthly returns within the past year (Max3) before the announcement. I define the lottery-like feature of the deal (Combined_Max3) as the weighted average Max3 from the acquirer and the target. Similar to the CEF setting, the tendency of the acquirer and the target hitting "jackpots" together (CoMax3) is defined as the percentage of top-three monthly returns that occur at the same month.

Consistent with my prediction, I find that the lottery-like feature of the deal has a significantly negative effect on the combined announcement-day return. After controlling for characteristics from acquirers, targets, and deals, the coefficient on Combined_Max3 is −1.280 (t-statistic = −2.24), which suggests that a one-standard deviation increase in the lottery-likeness of the deal is associated with 1.280% decrease in the combined announcement-day return. On the other hand, the interaction of Combined_Max3 and CoMax3 yields a significantly positive estimate of 0.744 (t-statistic = 4.00), suggesting that a one-standard deviation increase in the interaction term can offset the negative effect of Combined_Max3 by 0.744%.

The diversification of lottery-like features may also be relevant to the conglomerate discount: the average conglomerate is worth less than a portfolio of comparable single-segment firms (Lang and Stulz 1994; Berger and Ofek 1995). The idea is that investors pay a price premium for lottery-like single segment firms, but the conglomerate itself does not exhibit lottery-likeness. In addition, if these lottery-like single segment firms tend to hit “jackpots” together, the discount may be partially mitigated. I find consistent empirical evidence to support both predictions.

A potential concern with the effect of lottery-like stocks hitting “jackpots” together is that whether it is driven by the correlation of returns instead. To address this concern, I conduct three placebo tests (one for each setting) by replacing the CoMax variable with a measure of return correlation. To isolate the mechanical relation between CoMax and return correlation, I compute a non-Max return correlation by excluding the “jackpots” hit together (see Section 4.4 for detailed description). Then, I repeat the aforementioned analyses for all three settings using this non-Max return correlation, and find that it cannot explain the closed-end fund discount, the combined announcement-day return, or the conglomerate discount. These three exercises show that hitting “jackpots” together drives my results.

Since the diversification of lottery-like features destroys CEF prices, it is natural to wonder if fund managers are aware of this situation and try to avoid lottery-like stocks upon fund inceptions. I conduct additional tests based on propensity score matching to find out the answer. Specifically, for each of the top-ten holdings of a CEF at fund inception, I select 10 pseudo stocks which are similar to the actual holding by reference to a host of firm characteristics but are not selected by the fund. I construct stock pairs from the actual top-ten holdings and the 100 pseudo holdings, and compute Pair_Max5 and CoMax5 for each stock pair. Then I conduct logit regressions with dependent variable equals one if the stock pair is from the top-ten holdings, and zero otherwise. I find that increasing Pair_Max5 by one-standard deviation lowers the likelihood of the pair being included at the inception by 18.6% relative to the unconditional probability. On the other hand, increasing CoMax5 by one-standard deviation make the pair 30.0% more likely to be included at the inception relative to the unconditional probability.

Similarly, in the M&A setting, if a manager from a lottery-like acquirer (target) is aware that the diversification of lottery-like features destroys combined announcement-day return, he should find a lottery-like target (acquirer) that always hits “jackpots” together. I test this prediction by matching pseudo acquirers and pseudo targets to the M&A deals by reference to a host of firm characteristics. Then I computing Combined_Max3 and CoMax3 for both actual acquirer-target pairs and pseudo acquirer-target pairs. I conduct logit regressions with dependent variable equals one if the pair is from an actual M&A deal, and zero otherwise. I find that, acquirers (targets) with strong lottery-like features tend to choose a lottery-like target (acquirer) with strong tendency of hitting “jackpots” together. Increasing the interaction of Combined_Max3 and CoMax3 by one-standard-deviation makes the pair 29.2% (20.8%) more likely to announce an M&A deal relative to the unconditional likelihood. No such result is obtained for non-lottery-like acquirers (targets). If both the acquirer and the target are allowed to be pseudo firms, increasing the interaction of Combined_Max3 and CoMax3 by one-standard-deviation makes the pair 22.0% more likely to announce an M&A deal relative to the unconditional likelihood.

The rest of the paper is organized as follows: Section 2 places my study in the literature. Section 3 describes the data and main variables of interests. Sections 4 & 5 presents my findings. Section 6 concludes.

2. Background and Contribution

Barberis and Huang (2008) suggest that their framework can provide a unifying way of understanding a number of seemingly unrelated facts in stock markets: the long-term underperformance of an initial public offering stock (Green and Hwang, 2012); the low average return of “distressed” stocks (Campbell, Hilscher, and Szilagyi, 2008), of out-of-the-money options (Boyer and Vorkink, 2014), of stocks traded over the counter (Eraker and Ready, 2015); and the lack of diversification in household portfolios (Mitton and Vorkink, 2007; Goetzmann and Kumar, 2008). Inspired by their model implication that a lottery-like (i.e., positively skewed) stock can become overpriced relative to the prediction from the traditional expected utility model, I provide a novel and unifying explanation for three seemingly unrelated phenomena, i.e., the closed-end fund discount puzzle, the announcement-day returns of mergers and acquisitions, and the conglomerate discount.

This study is also related to the literature testing Barberis and Huang (2008)'s model. Existing empirical studies focus on testing the model implication that lottery-like stocks will earn negative average excess returns and find results supporting the theory (Boyer, Mitton, and Vorkink 2010; Bali, Cakici, and Whitelaw 2011; Conrad, Dittmar, and Ghysels 2013; Amaya, Christoffersen, Jacobs, and Vasquez 2015; Barberis, Mukherjee, and Wang 2016). However, skewness proxies can be correlated with firm fundamentals (such as size, book-to-market ratio, profitability, etc.), which have been well documented to predict the cross-section of stock returns.[2] Therefore, these firm fundamentals may potentially contribute to the negative average excess returns documented for lottery-like stocks.

This paper provides a unique methodology inspired by Barberis and Huang (2008)'s model and find evidence consistent with the model prediction. Specifically, Barberis and Huang (2008) show that a lottery-like stock can become overpriced relative to the prediction from the traditional expected utility model. However, when lottery-like stocks are bundled into a portfolio, the lottery features get diversified away, as long as they do not always hit "jackpots" together, leaving the portfolio itself non-lottery-like. Since lottery-like assets are traded at a price premium while non-lottery-like assets are not, the portfolio should be valued less than the total value of its components and traded at a discount.

Thus, my empirical strategy is to compare the difference between the value of a portfolio and the total value of its components, and link this pricing difference to the difference in lottery-like features between the portfolio and its components. By construction, the portfolio and its underlying components are nearly identical in terms of fundamental characteristics

[2] For example, Boyer, Mitton, and Vorkink (2010) use idiosyncratic volatility, momentum, turnover ratio, and firm size (among others) to compute their expected idiosyncratic skewness, making their measure mechanically correlated to these characteristics; Barberis, Mukherjee, and Wang (2016) reports that their "prospect theory value" has a correlation of 36% with size, −34% with book-to-market ratio, 32% with momentum, and 56% with long-term reversal.

such as size, growth options, past performance, etc. Yet they can differ strongly along the dimension of lottery-like feature. The aggregate portfolio does not offer lottery-like payoffs while its holdings can exhibit strong lottery-like features. As such, my approach provides a relatively more powerful setting to test the relevance of the lottery-like feature in determining asset prices.

3. Data and Variables

In this section, I introduce samples, dependent variables, proxies for lottery-like features and the tendency of hitting "jackpots" together, and controls for the CEF setting (Section 3.1), M&A setting (Section 3.2), and the conglomerate setting (Section 3.3).

3.1 Closed-end Funds

The first set of empirical tests focus on US equity closed-end funds. A closed-end fund (CEF) is organized as a publicly traded investment company issuing a fixed number of shares which are not redeemable from the fund. The majority of holding assets for a US equity closed-end fund are stocks traded in US stock exchanges. The nature that a CEF itself is traded in a stock exchange makes it possible for me to compare the market value of the fund with the total market value of the CEF's holding assets.

Following the literature on CEFs, I first extract a list of CEFs from The Center for Research in Security Prices (CRSP) by selecting securities with a share code ending in 4 (i.e., closed-end funds incorporated within US). Securities with share codes 14 (Ordinary Common Shares) and 44 (Shares of Beneficial Interest) are kept, while securities with share codes 24 (Certificates) and 74 (Depository Units, Units of Beneficial Interest, Units of Limited Partnership Interest, Depository Receipts, etc.) are deleted. The monthly CEF prices are available from CRSP, while the net asset value (NAV), which is the market value of a fund's underlying assets on a per-share basis, can be accessed from COMPUSTAT. The dependent variable is the CEF premium, which is defined as the difference between the closing price of the CEF and the its NAV, divided by NAV:

$$\text{Premium}_{i,t} = (\text{Price}_{i,t} - \text{NAV}_{i,t}) / \text{NAV}_{i,t} , \tag{1}$$

For example, a CEF traded at $4.9 but with a NAV of $5 is described to have a premium of −2%. In other words, the CEF is traded at 2% discount. To avoid unnecessary confusion, I always describe the results in terms of discount, following the common convention and the fact that the majority of CEFs trade at discounts. To avoid distortions on the CEF discount after the initial public offering and shortly before the winding up of a closed-end fund, I follow Chan, Jain, and Xia (2008) to exclude data within the first six months after a fund's IPO and in the month preceding the announcement of liquidation or open-ending of the fund.[3]

I obtain data on CEFs' holding positions from Morningstar.[4] CRSP and Morningstar data are merged by fund name and CUSIP. I focus on US equity closed-end funds.[5] In my analysis, I compute the independent variables of interests only for a fund's top-ten holdings. I do so because I conjecture that when investors evaluate whether they should invest in a fund from its holdings, they always focus on the portfolio's top-ten holdings, which are readily observable on the fund's website, factsheets, finance media, etc. The entire positions, on the other hand, is not likely to be available.

Following Bali, Cakici, and Whitelaw (2011), I proxy the lottery-like feature for both the CEF and each of its top-ten holdings by the average top five daily returns within the month (Max5). I choose this measure because it can capture the low probability and extreme payoff state described in Barberis and Huang (2008) and I conjecture that investors evaluate the performance of CEFs and their holding stocks in a short-term horizon. I assess the overall

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[3] Existing studies on the closed-end fund discount puzzle have shown that closed-end funds usually start out at a premium. Most of this premium is a natural derivative of the underwriting and startup costs, which are removed from the proceeds, thus reducing the NAV relative to the stock price. However, this premium gradually shifts to a discount (which becomes the norm thereafter) within the first six months after its initial public offering (Weiss, 1989). On the other hand, the share price of a CEF rises and the discount shrinks shortly before the termination of the fund, either through liquidation or open-ending (Brauer, 1984; Brickley and Schallheim, 1985). For a detailed summary of the closed-end fund puzzle, check Lee, Shleifer, and Thaler (1991). This exclusion has, however, very limited consequences on my results

[4] The majority of CEFs report their holdings at quarterly frequency, while others report bi-annually or monthly. Since the independent variables of interests can be constructed at monthly frequency, I utilize all available holding reports that meet the requirements.

[5] There exists no clear identification of a US equity CEF in the dataset. Therefore, I define a CEF to be a US equity CEF if at least 50% of its weight is invested in stocks listed in US stock exchanges. Generally speaking, equity CEFs usually hold some other securities as well, such as stock options, corporate bonds, treasury bills, foreign currencies, or cash & cash equivalents.

lottery-like feature of a CEF's holdings (Holding_Max5) by the portfolio-weighted average Max5 from each of the top-ten stocks. The difference between the lottery-like feature of a CEF (CEF_Max5) and the overall lottery-like feature of its holdings (Holding_Max5) is denoted as Ex_Max5 (= CEF_Max5 − Holding_Max5).

Another key empirical design is to capture the tendency of lottery-like stocks hitting "jackpots" together. As illustrated by the simplified example in the introduction, I need to construct this proxy at the level of each pair of stocks. Every CEF in each holding report has 45 possible pairs of stocks based on its top-ten holdings.[6] For each stock pair, I count the percentage of the top five daily returns from the two stocks that happen at the same day (CoMax5). For example, if the top five daily returns for stock A comes from day 1, day 4, day 9, day 11 and day 15 of the month, while the top five daily returns for stock B comes from day 2, day 4, day 9, day 14, and day 20 of the month, then CoMax5 equals 40% for the pair (A, B). In addition, the lottery-like feature of the pair is defined as the portfolio-weighted average Max5 from the two stocks (Pair_Max5).

The idea of lottery-like stocks hitting "jackpots" together is captured by the interaction of Pair_Max5 and CoMax5. Thus, a strong interaction indicates the empirical fact that the stock pair has a strong lottery-like feature, and the two stocks in the pair tend to hit "jackpots" together. This product is taken average across all possible 45 pairs, weighted by the sum of holding weights from both two stocks.

I consider the following control variables: disagreement among top-ten holdings, inverse price, dividend yield, expense ratio, liquidity ratio, excess skewness, and excess idiosyncratic volatility. Detailed descriptions of these variables can be found in the Appendix. I require that each observation should have non-missing value of the CEF discount, key independent variables described above, and all control variables. My final sample contains 101 CEFs from 2002 to 2014. The sample period is determined by the availability of Morningstar.

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[6] This is another reason why I focus my analysis on top-ten holdings. Since I need to work on every possible pair of stocks, the number of pairs I have to deal with will increase exponentially with the number of stocks. The average CEF in my sample holds 93 stocks, which means 4,278 possible stock pairs; the 90^{th} percentile is 201 stocks, which means 20,100 possible stock pairs. Focusing on the top ten holdings therefore dramatically reduces computation to a manageable level.

Panel A of Table 1 reports the summary statistics for the final CEF sample. The average CEF discount is about 4.7% with a standard deviation of 14.3%. The mean and standard deviation of the CEF discount is in line with those reported in prior studies (Bodurtha, Kim, and Lee, 1995; Klibanoff, Lamont, and Wizman, 1998; Chan, Jain, and Xia, 2008; Hwang, 2011; Hwang and Kim, 2017; Hwang, Lou, and Yin, 2017).

[Table 1 Here]

In Panel A of Table 2, I compare the lottery-like features of CEFs and holdings in my sample. The average Max5 for a CEF is about 1.4%, while the average Max5 for a holding stock is 2.2%. This −0.9% average difference (t-statistic = −34.44) in Max5 between CEFs and holdings is significant at all conventional levels. Results presented there show that the lottery-like feature of CEFs are indeed weaker than its holdings, which indicates that lottery-like features get diversified away when individual holdings are bundled into a portfolio.

[Table 2 Here]

3.2 Mergers and Acquisitions

The second set of empirical tests focus on M&A deals. I extract details on M&A deals from the Securities Data Corporation's (SDC) U.S. Mergers and Acquisitions database. Following Masulis, Wang, and Xie (2007), I require that: 1) the status of the deal must be completed; 2) the acquirer controls less than 50% of the target shares prior to the announcement; 3) the acquirer owns 100% of the target shares after the transaction; 4) the deal value disclosed in SDC is more than $1 million.

I obtain stock data and financial statements from CRSP and COMPUSTAT, respectively. These two datasets are merged with deal details from SDC based on CUSIP. The dependent variable is the combined announcement-day returns, defined as the average cumulative abnormal return over days [−1, +1] across the acquirer and the target, weighted by their market capitalization in the month prior to the announcement:

$$\text{Combined\_CAR}\,[-1,+1] = w_A \times \text{CAR}_A\,[-1,+1] + w_T \times \text{CAR}_T\,[-1,+1]\,, \qquad (2)$$

where t = 0 is the announcement day (or the ensuing trading day). Following standard literature, I use DGTW adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) to compute CAR [−1, +1]. Combined_CAR [−1, +1] captures the difference between the value of the joint firm (i.e., the value of the portfolio itself) and the total value of the acquirer and the target (i.e., the total value of the portfolio's components).

I use a proxy that is similar in essence as applied in the CEF setting to capture the lottery-like features of acquirers and targets. However, since M&A deals are the results of long-term evaluations and negotiations between both parties, I conjecture that investors would take a longer horizon to evaluate them. Taking this note, it may be counter-intuitive to produce a measure for lottery-like features based on daily returns in a monthly frequency. Therefore, I measure the lottery-like features from acquirers and targets based on the average of top-three monthly returns in the past year prior to the announcement of the deal (Max3).[7] The overall lottery-like feature of a deal is thus defined as the average Max3 across the acquirer and the target, weighted by their market capitalization in the month prior to the announcement (Combined_Max3).

Similar to the practice in the CEF setting, to capture the tendency of hitting "jackpots" together for each deal, I count the percentage of the top-three monthly returns that happen at the same month for the acquirer and the target (CoMax3). For example, if the top-three monthly returns for stock A come from month 2, month 5, and month10 before the month of the announcement, while the top-three monthly returns for stock B come from month 3, month 5, and month 9 before the month of the announcement, then CoMax3 equals 33% for this deal. The idea of lottery-like acquirer and target hitting "jackpots" together is captured by the product of Combined_Max3 and CoMax3. Thus, a strong interaction indicates the empirical fact that the deal has a strong lottery-like feature, and the acquirer and the target tend to hit "jackpots" together.

I consider the following control variables for both acquirers and targets: market capitalization, market-to-book ratio, return on assets (ROA), leverage, and operating cash

[7] Some existing studies also utilize monthly returns to capture the positively skewed return distribution, for instance, Mitton and Vorkink(2006), Barberis, Mukherjee, and Wang (2016).

flows. I consider the following control variables for each deal: disagreement, relative size, tender offer, hostile offer, competing offer, cash only, stock only, same industry, combined skewness, and combined idiosyncratic volatility. Detailed descriptions of these variables can be found in the Appendix.

My final sample contains 1,145 M&A deals from 1989 to 2014. Summary statistics for this sample can be found in Panel B of Table 1. The average combined announcement-day return in my sample is 1.6% with a standard deviation of 7.0%.

I compare the lottery-like feature of acquirers, targets, and deals in Panel B of Table 2. Targets have stronger lottery-like features than acquirers in the sample. The average Max3 for targets is 19.3%, while the averages of Max3 for acquirers is 15.1%. The average difference in Max3 between acquirers and targets is −4.2 (t-statistic = −11.63). The lottery-like feature of the target gets partially offset when evaluate at the M&A deal level.

3.3 Conglomerates

The last set of tests focus on conglomerates. A conglomerate is the combination of two or more corporations engaged in entirely different businesses (often different industries) that fall under one corporate group, usually involving a parent company and many subsidiaries.

My data on firm segments are from COMPUSTAT Historical Segments. This dataset provides business segments (an industry segment or product line reported by a company) for over 70% of the companies in the COMPUSTAT North American database since 1976. For each segment, firms report net sales and other accounting variables. In addition, COMPUSTAT assigns each business segments a four-digit SIC code based on the line of business description of the segment. I define a conglomerate as a firm with at least two segments (i.e., at least two different four-digit SIC code), and a single-segment firm as a firm with only one segment (i.e., only one unique four-digit SIC code). Following standard literature (Berger and Ofek, 1995; Lamont and Polk, 2001; Mitton and Vorkink, 2010), I discard firm-year observations if COMPUSTAT assigns any segment a 1-digit SIC code of 0 (Agriculture, Forestry and Fishing), 6 (Finance, Insurance and Real Estate), or 9 (Public

Administration & Nonclassifiable). I also drop firm-year observations that meet any of the following conditions: 1) total sales or total assets or book value of equity of the firm is missing or non-positive; 2) net sales for any of the segments is missing or non-positive; 3) the sum of segment sales is not within one percent of the total sales of the firm; 4) total sales of the firm is less than $20 million.

After screening out defective observations, I match the rest of the segment data to CRSP for stock level information. More specifically, I match book value from fiscal year $t-1$ to market value from June of calendar year t, and compute market-to-book ratios for all conglomerates and single-segment firms in the data accordingly. The average market-to-book ratio for each segment is defined as the sales-weighted average market-to-book values across all single-segment firms in the segment. The imputed market-to-book ratio (Imputed_MEBE) is defined as the average market-to-book ratio across all segments a conglomerate operates within, weighted by this conglomerate's net sales from each segment. The conglomerate premium is defined as the difference between a conglomerate's market-to-book ratio (MEBE) and its Imputed_MEBE, scaled by Imputed_MEBE:

$$\text{Premium}_{i,t} = (\text{MEBE}_{i,t} - \text{Imputed\_MEBE}_{i,t})/\text{Imputed\_MEBE}_{i,t}\,, \qquad (3)$$

Following prior literature, I winsorize this variable at the 1st and 99th percentiles. Similar to the practice in the CEF setting, to avoid unnecessary confusion, I always describe the results in terms of discounts (i.e., the conglomerate premium is negative), following the common convention and the fact that the majority of conglomerates trade at discounts. This variable captures the difference between the market value of a conglomerate and the overall market value of the segments related to this conglomerate but operating separately.

I take the same empirical strategy as M&A deals to capture lottery-like features in this setting. Lottery-like features for a conglomerate and its corresponding single-segment firms are proxied by the average top-three monthly returns in the past year before conglomerates' fiscal year-end (Max3). I conjecture that, when investors evaluate lottery-like features for all the single-segment firms associated with a conglomerate, they always focus on the most representative ones, which are more likely to be available. Therefore, I choose five most suited single-segment firms within each segment a conglomerate operates within. Single segment firms are evaluated by the closeness of SIC codes and net sales. The average Max3 for each segment is then defined as the sales-weighted average Max3 across these five single-segment firms. The imputed Max3 (Imputed_Max3) is defined as the average segment Max3 across all segments a conglomerate operates within, weighted by this conglomerate's net sales from each segment. The difference between a conglomerate's Max3 (Cong_Max3) and its Imputed_Max3 is denoted as Ex_Max3 (= Cong_Max3 – Imputed_Max3).

Trying to capture the tendency of two segments hitting "jackpots" together is somewhat tricky. To the best of my knowledge, previous literature provides little guidance on this attempt.[8] To have a similar proxy as the ones adopted in the CEF setting and the M&A setting, I construct a CoMax3 measure by first pairing segments and then pairing stocks within segment pairs. For example, consider a conglomerate which operates in three segments A, B, and C. This conglomerate has three segment pairs: (A, B), (A, C), and (B, C). In each segment pair, I have selected five single-segment firms, thus I can construct 25 (5×5) stock pairs (i.e., one stock from each segment). I count the percentage of top-three monthly returns that happen at the same month for each stock pair, and take weighted-average by sales across 25 pairs, and then take weighted-average by sales across 3 segment pairs.[9] This method is enlightened by Green and Hwang (2012), who pool returns from all stocks in a FF-30 industry to compute that industry's skewness. My method is essentially the same as theirs in the sense that I also pool a collection of individual stock returns to capture the lottery-like feature for a segment (industry).

The lottery-like feature of the pair is proxied by sales-weighted average Max3 from both stocks (Pair_Max3), and the idea of lottery-like segments hitting "jackpots" together is captured by the product of Pair_Max3 and CoMax3. Thus, a strong interaction indicates the

[8] The most obvious choice, which is using value-weighted average returns from each segment, does not serve the purpose here, for the same reason illustrated by the simplified example in the introduction of this paper. Aggregating returns at segment level diversify away the lottery-like features I want to capture. This is also related to the stylized fact that individual firms generally exhibit positively skewed return distributions while the aggregate return has a negatively skewed distribution.

[9] This is another reason why I select five single-segment firms from each segment. Since I need to pair segments first and then pair stocks in segment pairs, the number of total pairs of stocks I have to deal with will increase rapidly with the number of segments a conglomerate operates within and the number of stocks considered. Focusing on five stocks from each segment therefore dramatically reduces computation to a manageable level.

empirical fact that the stock pair has a strong lottery-like feature, and the two stocks tend to hit "jackpots" together. This product is then taken sales-weighted average first at stock pair level and then at segment pair level.

Control variables for this setting include: disagreement, total assets, leverage, profitability, investment ratio, excess skewness, and idiosyncratic volatility. Detailed descriptions of these variables can be found in the Appendix. As reported in Panel C of Table 1, my final sample contains 15,907 firm-year observations from 1977 to 2014. The average conglomerate discount in my sample is 13.0%, which is in line with the figures reported in prior literature (Berger and Ofek, 1995; Lamont and Polk, 2001, Mitton and Vorkink, 2010).

Panel C of Table 2 compares the lottery-like feature of conglomerates and that of their associated single-segment firms. The average Max3 from conglomerates is 14.3%, while the average Max3 from their associated single-segment firms is 16.2%. The difference of −1.9% (t-statistic = −32.08) is significant at all conventional levels.

4. Main Results

In this section, I document empirical evidence based on three samples. Section 4.1 summarizes results on the CEF setting; Section 4.2 describes results on the M&A setting; Section 4.3 reports analysis on the conglomerate setting; Section 4.4 discusses placebo tests.

4.1 Closed-end Funds

I first conduct tests on the sample of CEFs. I estimate pooled OLS regressions with fixed effects and standard errors clustered along both fund and time dimensions. The dependent variable is the CEF premium (in percentage). The independent variables of particular interests are Ex_Max5 (the difference between the lottery-like feature of the CEF and the overall lottery-like feature of its top-ten holdings) and Pair_Max5×CoMax5 (the tendency of lottery-like stocks hitting "jackpots" together). Control variables include disagreement among top-ten holdings, inverse price of the CEF, dividend yield, liquidity ratio, the rank of expense ratio, excess skewness, and the rank of excess idiosyncratic volatility. Detailed descriptions of control variables can be found in the Appendix. Hwang (2011) argues that inverse price and dividend yield have differential predictions on the CEF premium depending on whether the fund trades at a discount or at a premium. Therefore, I follow his paper and separate inverse price into two variables: *Inverse Price[pos]*, which equals the inverse price if the fund trades at a premium and zero otherwise; and *Inverse Price[neg]*, which equals inverse security price if the fund trades at a discount and zero otherwise. I do the same for dividend yield and separate it into *Dividend Yield[pos]*, and *Dividend Yield[neg]*. All independent variables are standardized to have mean zero and standard deviation of one. Regression results are reported in Table 3.

[Table 3 Here]

The first three columns test whether a CEF with stronger lottery-like holdings tend to trade at a bigger discount. The lottery-like feature of the CEF is controlled by using the relative lottery-likeness, i.e., Ex_Max5, which is the difference between the lottery-like feature of the CEF (CEF_Max5) and the portfolio-weighted average lottery-like feature of its top-ten holdings (Holding_Max5). Previous analysis predicts a positive and significant coefficient on CEF_Max5, because the stronger lottery-like feature a CEF's top-ten holdings exhibit relative to the fund itself (i.e., higher Holding_Max5, lower CEF_Max5), the bigger discount this CEF should be traded at (i.e., lower premium). In Columns 1 and 2, I control time fixed effects, while in Column 3, I control both fund and time fixed effects. Time fixed effects can help control for time-varying trends, such as the fluctuation of investor sentiments, while fund fixed effects can help control cross-sectional differences.

Column 1 confirms my prediction: the estimate on Ex_Max5 is both positive (4.794) and significant (t-statistic = 3.39). This result remains significant after including all control variables (Column 2) and fund fixed effects (Column 3). Column 3 suggests that a one-standard deviation increase in the relative lottery-likeness of a CEF's holdings comes with 0.990% increase in the CEF discount. For reference, the average CEF discount in my sample is 4.7%. Therefore, the effect on Ex_Max5 is not only statistically significant, but also economically large. That being said, I am not trying to rule out other possible explanations for the CEF discount, but offering a novel and interesting perspective to revisit this well-documented puzzle.

The key innovative empirical design is to test the diversification of lottery-like features at the stock pair level. If the evidence discovered in Column 1-3 are indeed due to the reason that lottery-like stocks are relatively overpriced and lottery-like features of the holdings are diversified away for the CEF, I should find a second-order effect which goes against the result on Ex_Max5: if a CEF's top-ten holdings exhibit strong lottery-like feature and they tend to hit "jackpots" together, the CEF discount should be partially mitigated. Column 4-7 test this prediction.

I capture the tendency of lottery-like stocks hitting "jackpots" together at the level of stock pairs. Every CEF in each holding report has 45 possible pairs of stocks based on its top-ten holdings. For each stock pair, I count the percentage of the top five daily returns that happen at the same day (CoMax5). In addition, the lottery-like feature of the pair is defined as the average Max5 from the two stocks, weighted by portfolio weights (Pair_Max5). Thus, the idea of lottery-like stocks hitting "jackpots" together is captured by the product of Pair_Max5 and CoMax5. This product is taken average across all possible 45 pairs, weighted by the sum of portfolio weights from both two stocks (denoted as Pair_Max5×CoMax5).

To conduct these additional tests, I first decompose Ex_Max5 into Holding_Max5 and CEF_Max5 and report the time-fixed effect regression results in Column 4. This practice should be essentially the same as Column 1, but with a different way to control the lottery-like feature of the CEF. Consistent with the results in Column 1, the estimate on Holding_Max5 is negative and significant. The net effect, which in this case should be the sum of the estimate on Holding_Max5 and CEF_Max5 is negative. In Column 5, I introduce Pair_Max5×CoMax5 and CoMax5 into the regression. As predicted, the regression coefficient on the interaction term is both positive (1.170) and significant (t-statistic = 2.50). This result is robust after including control variables (Column 6) and fund fixed effect (Column 7). Column 7 shows that a one-standard-deviation increase in the interaction term will offset the CEF discount by 0.520% (t-statistic = 2.92). In other words, holding stocks with not only strong lottery-like features but also with strong tendency to hit "jackpots" together indeed brings a CEF's price closer to its net asset value per share.

Empirical evidence presented in this section shows that a CEF is traded at a lower price compared to its components because it holds overpriced lottery-like stocks, and lottery-like features of its holdings get diversified away for the fund. Since the CEF and its underlying components are different strongly along the dimension of lottery-like feature yet nearly identical in terms of fundamental characteristics, these results provide support to the theoretical work of Barberis and Huang (2008) from a unique setting which isolates the effect of lottery-like features on determining asset prices from firm fundamentals.

4.2 Mergers and Acquisitions

I estimate a pooled OLS regression with time-fixed effects and standard errors clustered by time across the 1,145 M&A events that meet data requirements. The dependent variable is the combined announcement-day return Combined_CAR [−1, +1] (in percentage), where t = 0 is the announcement day (or the ensuring trading date). It captures the difference between the market value of the combined firm (i.e., the portfolio) and the total market value of the acquirer and the target (i.e., the portfolio's components). The independent variables of interests are Combined_Max3 (the lottery-like feature of the deal) and Combined_Max3×CoMax3 (lottery-like acquirer and target hitting "jackpots" together). Control variables include characteristics from acquirers, targets and deals. Detailed description for all control variables can be found in the Appendix. All variables are standardized to have a mean of zero and a standard deviation of one. Regression results are reported in Table 4.

[Table 4 Here]

To start with, in Column 1 of Table 4, I put Combined_Max3 in the pooled OLS regression with time-fixed effects. The estimate on Combined_Max3 is −0.990 with a t-statistic of −1.93. After controlling various characteristics from acquirers, targets and deals, the estimate becomes stronger at −1.280 with a t-statistic of −2.24. This suggest that a one-standard-deviation increase in the lottery-like feature of the deal come with a 1.280% lower combined announcement-day return. Provided the mean combined announcement-day return in my sample is only 1.6%, this effect is both statistically and economically significant. These results confirm my prediction that the combined firm is valued less because the lottery-like features from the acquirer and the target are diversified away from the M&A deal.

Next, I test the effect of lottery-like acquirer and target hitting "jackpots" together on the combined announcement-day return. Similar to the practice in the CEF setting, to capture the tendency of hitting "jackpots" together in each deal, I count the percentage of the top-three monthly returns that happen at the same month for the acquirer and the target (CoMax3). The idea of lottery-like acquirer and target hitting "jackpots" together in this setting is captured by Combined_Max3×CoMax3. Thus, a strong Combined_Max3×CoMax3 indicates the empirical fact that the deal has a strong lottery-like feature, and the acquirer and the target tend to hit "jackpots" together. Columns 3 and 4 presents regression coefficients with the inclusion of Combined_Max3×CoMax3.

In Column 3, I conduct pooled OLS regressions with time-fixed effects by regressing Combined_CAR [−1, +1] on Combined_Max3×CoMax3, Combined_Max3, and CoMax3. As predicted, the estimate on the interaction term is positive (0.624) and significant (t-statistic = 3.30) at all conventional levels. This pattern is quite robust after including control variables (Column 4). As shown in Column 4, a one-standard-deviation increase in Combined_Max3×CoMax3 increases the combined announcement-day return by 0.744% (t-statistic = 4.00)

Results on M&A deals demonstrate that a combined firm is valued less than the total value of the acquire and the target, because lottery-like features from the acquirer and the target get diversified away due to M&A.

4.3 Conglomerate Firms

My final analysis focus on conglomerates. Similar to the other two settings, I estimate pooled OLS regressions with time fixed effects and standard errors clustered by firm and time. The dependent variable is the conglomerate discount computed on an annual basis. This variable captures the difference between the market value of a conglomerate (i.e., the portfolio) and the average market value of a set of comparable single-segment firms (i.e., the portfolio's components). The independent variables of interests are Ex_Max3 (defined as the difference between the lottery-like feature of a conglomerate and the overall lottery-like feature of all the segments the conglomerate operates within) and Pair_Max3×CoMax3 (lottery-like segments hitting "jackpots" together). Trying to capture the tendency of two segments hitting "jackpots" together is somewhat tricky. As outlined in Section 3, I construct CoMax3 and Pair_Max3×CoMax3 by first pairing segments and then pairing stocks within segment pairs. All independent variables are standardized to have a standard deviation of one. Regression results are reported in Table 5.

[Table 5 Here]

The first two columns of Table 5 test the effect of Ex_Max5 first. The estimate on Ex_Max3 is both positive and significant. This indicates that, if segments exhibit strong lottery-like features relative to the conglomerate, the conglomerate discount is more severe. In Columns 3-5, I decompose Ex_Max3 into Imputed_Max3 and Cong_Max3, and include Pair_Max3×CoMax3 in the regression. The results are as expected: the estimate on Pair_Max3×CoMax3 is significantly positive. Column 5 shows that a one-standard-deviation increase in Pair_Max3×CoMax3 will partially offset the conglomerate discount by 7.37% (t-statistic = 3.11).

4.4 Placebo Tests

A potential concern with CoMax results I have documented in Sections 4.1-4.3 is that whether this effect is driven by return correlations. To address this concern, I conduct three placebo tests (one for each setting), replacing the CoMax variable with a measure of return correlation. To isolate the mechanical effect of CoMax on return correlation, I compute return correlation by excluding the concurrent extreme returns.

Specifically, in the CEF setting, for each stock pair from a CEF's top-ten holdings, I get the daily return series for both stocks and exclude the Max returns that happen at the same days. The non-Max return correlation for the pair is computed using the rest of returns. Non_Max_Corr, i.e., the variable served as the "placebo", is constructed as the weighted average return correlation for all stock pairs. In addition, I calculate the weighted average of Max5 for the stock pair, and multiply this value to the return correlation of the stock pair. The interaction term served as the "placebo" (Pair_Max5×Non_Max_Corr) is constructed as the weighted average of all these products for every CEF at each report date. Then, I repeat the analyses in Section 4.1 for the CEF sample, and report the results in Panel A of Table 6.

[Table 6 Here]

In sharp contrast to Column 4-7 in Table 3, the interaction term (Pair_Max5×Non_Max_Corr) has no explanatory power on the CEF discount. The coefficients are neither statistically significant nor economically large. The results on Holding_Max5, however, remains.

Similar practice is also conducted on the M&A sample. I get the monthly return series from the past year for both the acquire and the target, and exclude the Max returns that happen at the same month. Then, I calculate the non-Max return correlation (Non-Max-Corr) between the acquirer and the target using the rest of the monthly returns as the "placebo" for CoMax3. The "placebo" interaction term is Combined_Max3×Corr. Compared to Columns 3 and 4 in Table 4, in Panel B of Table, Combined_Max3×Non_Max_Corr provides no robust power explaining the combined announcement-day return.

The last placebo test is conducted on the sample of conglomerates. For each stock pair within each segment pair, I get the monthly return series from the past year for both stocks, and exclude the Max returns that happen at the same month. The non-Max return correlation of the pair is calculated using the rest of returns. Non_Max_Corr, the "placebo" variable, is the sales-weighted average of these return correlations at the stock-pair level and then the segment pair level. The interaction term served as the "placebo" (Pair_Max5×Non_Max_Corr) is constructed as the sales-weighted average of all Pair_Max5×Non_Max_Corr across every stock pair and then across ever segment pair. As shown in Panel C of Table 6, the results in Table 5 disappear by replacing CoMax3 with Corr.

All placebo tests from this section show that the concurrence of extreme returns (CoMax) drive the results documented in the previous sections, not return correlations. This evidence further supports the theoretical work of Barberis and Huang (2008) by showing that the low probably of extreme payoff state is the primary reason driving the overpricing of lotter-like stocks.

5. Further Discussion

Since lottery-like features destroy CEF prices and combined M&A announcement returns, it is natural to wonder if managers from funds and firms are aware of this situation. If they are indeed aware of this, have they done anything to mitigate the effect? This section tries to shed some lights on these two questions.[10]

To the extent that fund managers are aware of the negative effect produced by high Max and low CoMax stocks, managers initiating a CEF should avoid selecting lottery-like stocks with low CoMax to maximize the proceeds from the IPO. To test this conjecture, I conduct the following experiment. For each top-ten stock in a fund's portfolio at inception, I identify ten pseudo top-ten stocks that are not selected by the fund, but are very similar to the top-ten holdings. Specifically, I apply propensity score matching based on firm size, book-to-market ratio and past twelve months' return and find ten pseudo stocks with the closest propensity scores for each of the real top-ten holdings. Therefore, a CEF at inception can produce 45 actual top-ten stock pairs and 4500 pseudo pairs. I estimate a pooled logit regression, where the dependent variable equals one if the stock pair consist of two actual top-ten holdings, and zero otherwise. My independent variables include the lottery-like feature of the stock pair (Pair_Max5, i.e., the portfolio-weighted average Max5 of both stocks in the pair), the tendency of hitting "jackpots" together (CoMax5), "co-maxing out" (Pair_Max5×CoMax5), the average market capitalization of the stock pair, the average book-to-market ratio of the stock pair, and the average past twelve months' return of the stock pair. All independent variables are normalized to have a standard deviation of one, and standard errors are clustered

[10] This analysis is not applicable to the conglomerate setting.

by time. Results are reported in Panel A of Table 7.

[Table 7 Here]

Column 1 from Panel A of Table 7 shows that CEF managers avoid stock pairs with strong lottery-like features.[11] The estimate on Pair_Max5 is −0.239 (z-statistic = −6.83) and significant at all conventional levels. Increasing Pair_Max5 by one-standard deviation lowers the likelihood of the pair being included at the inception by 18.6% relative to the unconditional probability. This evidence shows that CEF managers avoid to select stocks with strong lottery-like features at inception, provided other characteristics the same.

Column 2 of Panel A includes CoMax5 and Pair_Max5×CoMax5 in the regression. The estimate on CoMax5 is −0.249 (z-statistic = −3.81). This indicates that, increasing CoMax5 by one-standard deviation make the pair 30.0% more likely to be included at the inception relative to the unconditional probability.

A similar exercise can be conducted on M&A deals as well. To the extent that firm managers recognize the negative effect of lottery-like feature diversification and the combined announcement-day return, acquirers (targets) with strong lottery-like features should be more likely to find lottery-like targets (acquirers) with strong tendency of hitting "jackpots" together.

In Columns 1 and 2 of Panel B Table 7, I match each actual acquirer in my M&A sample with ten pseudo targets that are not involved in the M&A deal with this actual acquirer. Pseudo targets are determined similarly in the previous exercise, through the method of propensity score matching with reference to the same set of acquirer characteristics, target characteristics, and relative size used in the Section 3.2. These pseudo targets are the closest to the actual target based on the propensity scores. I pool these pseudo M&A pairs with the real pairs together, and run pooled logit regressions where the dependent variable equals one for actual M&A pairs, and zero otherwise. The independent variables are the lottery-like feature of the pair (Combined_Max3), the tendency of hitting "jackpots" together (CoMax3), and their

[11] Similar results can also be obtained if the regression is conducted at stock level instead of pair level.

interaction (Combined_Max3×Comax3).

If managers from acquirers are indeed aware of the negative effect of lottery-like feature diversification on the combined firm, managers from acquirers which have exhibited lottery-like features should find lottery-like targets which tend to hit "jackpots" with acquirers together. On the other hand, managers from acquirers with low lottery-like features may not put too much weight on this issue. Therefore, I divide the sample into two groups based on acquirers' Max3. Column 1 reports regression results based on the subsample of non-lottery-like acquirers, while Column 2 reports regression results based on the subsample of lottery-like acquirers. These results confirm my prediction that a manager from a lottery-like acquirer indeed tend to find a lottery-like target with a high CoMax3. As reported in Column 2, the estimate on Combined_Max3×Comax3 is 0.288 (z-statistic = 2.48). This indicates that increasing the interaction by one-standard-deviation makes the pair 29.2% more likely to announce an M&A deal relative to the unconditional likelihood. No such result is obtained when acquirers have low lottery-like features.

In Columns 3 and 4 of Panel B Table 7, I repeat the analysis in Columns 1 and 2, but match each actual target in my M&A sample with ten pseudo acquirers that are not involved in the M&A deals. Similarly, if managers from targets are indeed aware of the negative effect of lottery-like feature diversification on the combined firm, managers from lottery-like targets should find lottery-like acquirers which tend to hit "jackpots" together. This is exactly what I document in Column 4. The estimate on Combined_Max3×CoMax3 is 0.183 (z-statistic = 2.36). This indicates that increasing the interaction of Combined_Max3 and CoMax3 by one-standard-deviation makes the pair 20.8% more likely to announce an M&A deal relative to the unconditional likelihood.

As a last practice on the M&A setting, I combined the procedures in Columns 1-4 by including stock pairs consists of both pseudo acquires and pseudo targets. Thus, for each deal, I have 121 stock pairs (11×11), in which only one pair is the real M&A deal. I find consistent results with previous findings. In Column 5, the estimate on Combined_Max3×CoMax3 is 0.166 (z-statistic = 2.07). This indicates that increasing the interaction of Combined_Max3 and CoMax3 by one-standard-deviation makes the pair 22.0% more likely to announce an

M&A deal relative to the unconditional likelihood.

To conclude, results from Table 7 indicate that mangers from CEFs and M&A firms are aware that the diversification of lottery-like features destroy the market value of CEFs and combined firms, and they have taken actions to mitigate the effect. Provided everything else equal, CEF managers tend to avoid lottery-like stocks at fund inceptions, while lottery-like acquirers (targets) tend to select lottery-like targets (acquires) with high CoMax when getting into M&A deals. These results shows that the effect of diversification in lottery-like features affects managerial decisions.

6. Conclusion

This paper builds upon Barberis and Huang (2008)'s implication that lottery-like stocks can become overpriced relative to the prediction of the expected utility model. Inspired by this, I argue that a portfolio holding lottery-like stocks should be valued less than the total value of its components, because lottery-like features get diversified away when lottery-like stocks do not hit "jackpots" together. I present evidence supporting this argument and provide a novel and unifying explanation for the closed-end fund discount puzzle, the announcement-day returns of mergers and acquisitions, and the conglomerate discount.

My paper provides a unique setting to test the effect of lottery-like features on security pricing. Since stocks are combined and traded "as a package", the portfolio itself provides the same fundamental characteristics as its holdings except for return distributions. Therefore, any pricing difference observed between the portfolio and the sum of its components is most likely driven by the discrepancy in lottery-like features between the portfolio and its holdings.

My paper also has managerial implications. In particular, my argument implies that, in the presence of diversification in lottery-like features, fund managers are better off separating their large portfolios into smaller portfolios and more focused stocks that have strong tendency to hit "jackpots" together. When evaluating potential M&A deals, lottery-like firms' managers should take advantage of their lottery-like features by finding a lottery-like counterparty with high tendency to hit “jackpots” together. Finally, it may be beneficial for conglomerates to unbundle their giant business empire into smaller firms with more focused business.

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Appendix. Descriptions on Control Variables

A1. Closed-end Funds

Disagreement: The portfolio-weighted average price-scaled earnings forecast dispersion of the top-ten stocks held by the CEF.

Inverse Price: The inverse of the CEF's market price.

Dividend Yield: The sum of the dividends paid by the CEF over the past one year, divided by the CEF's market price.

Liquidity Ratio: The CEF's one-month turnover, divided by the portfolio-weighted average one-month turnover of the stocks held by the CEF. If the stock is listed on NASDAQ, we divide the number of shares traded by two.

Expense Rank: All CEFs in the sample are ranked into five groups based on their expense ratio. The ones with the highest expense ratio get a rank of 5, while the ones with the lowest expense ratio get a rank of 1.

Excess Skewness: The difference between the return skewness of the CEF and the portfolio-weighted average return skewness of the stocks held by the CEF. Return skewness is calculated as $s = (1/22) \times \sum_t (r_t - \mu)^3 / \sigma^3$, where s is calculated using daily returns over a one-month return window, μ is the mean return, and σ^3 is the cube of the return standard deviation.

Excess Idiosyncratic Volatility Rank: The difference between the idiosyncratic volatility of the CEF and the portfolio-weighted average idiosyncratic volatility of the stocks held by the CEF. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-month return window using daily returns. All CEFs in the sample are further ranked into five groups based on excess idiosyncratic volatility. The ones with the highest value get a rank of 5, while the ones with the lowest value get a rank of 1.

A2. Mergers and Acquisitions

Disagreement: The average earnings forecast dispersion (scaled by price) across the acquirer and the target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement.

Acquirer (Target) Market Capitalization: The acquirer's (target's) market capitalization in the month prior to the announcement.

Acquirer (Target) Market-to-Book Ratio: The acquirer's (target's) market-to-book ratio.

Acquirer (Target) ROA: The acquirer's (target's) ratio of earnings before interest and tax to total assets.

Acquirer (Target) Leverage: The acquirer's (target's) ratio of long-term debt to total assets.

Acquirer (Target) Operating Cash Flow: The acquirer's (target's) ratio of operating cash flows to total assets.

Relative Size: The market capitalization of the acquirer over the sum of market capitalization from the acquirer and the target.

Tender Offer: Variable that equals one if a tender offer is made, and zero otherwise.

Hostile Offer: Variable that equals one if the takeover is considered hostile, and zero otherwise.

Competing Offer: Variable that equals one if there are multiple offers made by various companies, and zero otherwise.

Cash Only: Variable that equals one if the acquirer only uses cash to purchase the target, and zero otherwise.

Stock Only: Variable that equals one if the acquirer only uses stocks to purchase the target, and zero otherwise.

Same Industry: Same industry is a dummy variable that equals one if the acquirer and target companies are in the same two-digit SIC code, and zero otherwise.

Combined Skewness: The average return skewness across the acquirer and the target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement. Return skewness is calculated as $s = (1/12) \times \sum_t (r_t - \mu)^3 / \sigma^3$, where s is calculated using monthly returns over a one-year return window, μ is the mean return, and σ^3 is the cube of the return standard deviation.

Combined Idiosyncratic Volatility Rank: The average idiosyncratic volatility across the acquirer and the target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-month return window using daily returns. All deals in the sample are further ranked into five groups based on excess idiosyncratic volatility. The ones with the highest value get a rank of 5, while the ones with the lowest value get a rank of 1

A3. Conglomerates

Disagreement: For each segment the conglomerate operates in, we calculate the average price-scaled earnings forecast dispersion across all single-segment firms in that segment. Disagreement is the sales-weighted average of those segment dispersions.

Total Assets: The conglomerate's total assets.

Leverage: The ratio of long-term debt to total assets.

Profitability: The ratio of earnings before interest and tax to net revenue.

Investment Ratio: The ratio of capital expenditure to net revenue.

Excess Skewness: The difference between the return skewness of the conglomerate and its imputed return skewness. Return skewness is calculated as $s = (1/12) \times \sum_t (r_t - \mu)^3 / \sigma^3$, where s is calculated using monthly returns over a one-year return window, μ is the mean return, and σ^3 is the cube of the return standard deviation. For each segment the conglomerate operates in, we compute the average skewness across all single-segment firms in that segment. The imputed return skewness is the sales-weighted average segment skewness.

Excess Idiosyncratic Volatility Rank: The difference between the idiosyncratic volatility of the conglomerate and its imputed idiosyncratic volatility. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-year return window using monthly returns. For each segment the conglomerate operates in, we compute the average idiosyncratic volatility across all single-segment firms in that segment. The imputed idiosyncratic volatility is the sales-weighted average of those segment volatilities. All conglomerates in the sample are further ranked into five groups based on excess idiosyncratic volatility. The ones with the highest value get a rank of 5, while the ones with the lowest value get a rank of 1.

Table 1 Descriptive Statistics

This table presents descriptive statistics for three samples. Panel A reports descriptive statistics for the sample of closed-end funds; Panel B reports descriptive statistics for the sample of mergers and acquisitions (M&A); Panel C reports descriptive statistics for conglomerates. The definitions of all variables are described in the appendix.

Panel A: Closed-end Funds						
Variables	N	Mean	StdDev	p25	p50	p75
CEF Premium	2330	-0.047	0.143	-0.124	-0.090	-0.025
Ex_Max5	2330	-0.006	0.007	-0.009	-0.006	-0.003
Holding_Max5	2330	0.020	0.010	0.014	0.017	0.022
CEF_Max5	2330	0.014	0.010	0.008	0.011	0.015
CoMax5	2330	0.445	0.102	0.372	0.436	0.512
Pair_Max5×CoMax5	2330	0.063	0.129	0.026	0.039	0.062
Disagreement	2330	0.001	0.001	0.001	0.001	0.001
Inverse Price	2330	0.094	0.068	0.055	0.075	0.107
Dividend Yield	2330	0.083	0.048	0.061	0.083	0.100
Expense Ratio	2330	0.013	0.007	0.010	0.012	0.014
Liquidity	2330	0.460	0.384	0.244	0.380	0.576
Ex_Tskew	2330	-0.405	0.753	-0.734	-0.313	0.015
Ex_Ivol	2330	-0.004	0.006	-0.007	-0.004	-0.002
Panel B: Mergers and Acquisitions						
Variables	N	Mean	StdDev	p25	p50	p75
Combined CAR [-1,+1]	1145	0.016	0.070	-0.017	0.010	0.047
Combined_Max3	1145	0.154	0.099	0.091	0.129	0.186
CoMax3	1145	0.380	0.256	0.333	0.333	0.667
Combined_Max3×CoMax3	1145	0.062	0.068	0.023	0.046	0.081
Disagreement	1145	0.002	0.007	0.000	0.001	0.002
Acq_MktCap ($M)	1145	22543	49701	1378	4509	17441
Acq_MEBE	1145	4.278	6.342	1.818	2.873	4.923
Acq_RoA	1145	0.105	0.096	0.053	0.103	0.157
Acq_Leverage	1145	0.538	0.210	0.378	0.545	0.672
Acq_OCF	1145	0.101	0.091	0.048	0.105	0.153
Tgt_MktCap ($M)	1145	1899	5755	173	464	1425
Tgt_MEBE	1145	3.972	17.238	1.460	2.255	3.539
Tgt_RoA	1145	0.047	0.160	0.016	0.070	0.122
Tgt_Leverage	1145	0.484	0.245	0.271	0.483	0.667
Tgt_OCF	1145	0.057	0.138	0.017	0.073	0.126
Relative Size	1145	0.831	0.160	0.722	0.890	0.962
Combined_Tskew	1145	0.150	0.642	-0.238	0.147	0.549
Combined_Ivol	1145	0.076	0.048	0.045	0.065	0.095

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Panel C: Conglomerates						
Variables	N	Mean	StdDev	p25	p50	p75
Conglomerate Firm Premium	15907	-0.130	0.981	-0.583	-0.292	0.171
Ex_Max3	15907	-0.014	0.105	-0.044	-0.005	0.021
Imputed_Max3	15907	0.157	0.111	0.092	0.129	0.187
Cong_Max3	15907	0.143	0.053	0.109	0.133	0.166
CoMax3	15907	0.329	0.087	0.270	0.320	0.380
Pair_Max3×CoMax3	15907	0.027	0.014	0.017	0.024	0.032
Disagreement	15907	0.050	0.052	0.015	0.032	0.066
Total Asset ($M)	15907	3507	8402	89	342	1632
Leverage	15907	0.201	0.156	0.071	0.183	0.299
Profitability	15907	0.072	0.096	0.032	0.072	0.116
Investment Ratio	15907	0.076	0.104	0.024	0.044	0.080
Ex_Tskew	15907	-0.077	0.869	-0.610	0.050	0.489
Ex_Ivol	15907	-0.011	0.056	-0.030	0.000	0.020

Table 2

This table compares lottery-like feature proxies for three samples. In the sample of closed-end funds (Panel A), lottery-like feature is proxied by the average of top five daily return within the month (Max5).; In the sample of mergers and acquisitions (Panel B) and the sample of conglomerate firms (Panel C), lottery-like features are proxied by the average of top-three monthly returns from the past year (Max3). T-statistics are provided in the brackets.

Panel A: CEF					
	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
Distribution of Holdng's Max5	0.022	0.016	0.013	0.018	0.030
Distribution of CEF's Max5	0.014	0.010	0.008	0.011	0.015
CEF's Max5 – Holding's Max5	-0.009				
	(-34.44)				
Panel B: Mergers and Acquisitions					
	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
Distribution of Target's Max3	0.193	0.132	0.114	0.158	0.235
Distribution of Acquirer's Max3	0.151	0.105	0.086	0.126	0.185
Distribution of Combined Max3	0.154	0.099	0.091	0.129	0.186
Combined Max3 - Target's Max3	-0.039				
	(-12.34)				
Acquire's Max3 - Target's Max3	-0.042				
	(-11.63)				
Panel C: Conglomerate Firms					
	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
Distribution of Single Segment Firm's Max3	0.162	0.103	0.106	0.140	0.198
Distribution of Conglomerate Firm's Max3	0.143	0.053	0.109	0.133	0.166
Conglomerate Firm's Max3 - Single Segment Firm's Max3	-0.019				
	(-32.08)				

Table 3 Closed-end Fund Premium/Discount

This table reports coefficient estimates from regressions of closed-end fund (CEF) premia on measures of the lottery-like features. The dependent variable is the difference between the CEF's market price and the CEF's NAV, divided by NAV (expressed in %). Lottery-like feature is proxied by the average of the top five daily returns within the month (Max5), following Bali, Cakici, and Whitelaw (2011). Ex_Max5 is the difference between a CEF's Max5 and the weighted average Max5 of its top 10 holdings. I construct CoMax5 and Pair_Max5×CoMax5 as follow: for each stock pair from a CEF's top ten holdings, I count the percentage of the top five daily returns from the two stocks that occur at the same time (CoMax5). In addition, I calculate the weighted average of MAX5 for the stock pair (Pair_Max5). The idea of lottery-like hitting "jackpots" together is captured by Pair_Max5×CoMax5. These variables are taken average at fund level across all stock pairs, weighted by the sum of portfolio weights from both stocks in the pair. Detailed description of all control variables can be found in the appendix. All independent variables are standardized to have a standard deviation of one. I estimate fixed effect panel regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: CEF Premium						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ex_Max5	4.794***	1.068**	0.990***				
	(1.416)	(0.486)	(0.352)				
Holding_Max5				-7.170***	-7.906***	-2.065**	-1.211***
				(2.537)	(2.483)	(0.944)	(0.409)
CEF_Max5				6.678***	6.256***	1.357*	1.647**
				(1.759)	(1.895)	(0.777)	(0.662)
Pair_Max5×CoMax5					1.170**	1.003**	0.520***
					(0.468)	(0.402)	(0.178)
CoMax5					0.0726	-0.624	-0.802**
					(0.933)	(0.463)	(0.381)
Disagreement		-0.0724	0.862*			-0.196	0.727
		(0.504)	(0.484)			(0.587)	(0.474)
Inverse Price[pos]		3.794**	-0.423			3.530*	-0.488
		(1.934)	(1.605)			(1.922)	(1.545)
Inverse Price[neg]		-1.338**	-3.878***			-1.435***	-3.909***
		(0.544)	(1.415)			(0.513)	(1.422)
Dividend Yield[pos]		5.245***	1.275			5.580***	1.281
		(1.530)	(1.544)			(1.475)	(1.483)
Dividend Yield[neg]		0.462	-0.726			0.689	-0.749
		(0.668)	(0.754)			(0.619)	(0.733)
Liquidity		0.368	-1.131**			0.503	-1.109**
		(0.539)	(0.498)			(0.529)	(0.483)
Expense_Rank		1.130**	-0.199			1.090*	-0.242
		(0.570)	(0.567)			(0.593)	(0.586)
Ex_Tskew		-0.637	0.438			-0.683	0.449
		(0.488)	(0.549)			(0.479)	(0.554)
Ex_Ivol_Rank		1.636***	0.742**			1.554***	0.853**
		(0.424)	(0.375)			(0.402)	(0.381)
Fixed Effect	Time	Time	Fund, Time	Time	Time	Time	Fund, Time
Observations	2,330	2,330	2,330	2,330	2,330	2,330	2,330
R-squared	0.257	0.695	0.855	0.257	0.262	0.699	0.857

Table 4 Combined M&A Announcement Day Returns

This table reports coefficient estimates from regressions of combined M&A announcement day returns on lottery-like features. The dependent variable is combined cumulative abnormal return (Combined CAR [−1,+1]), where t=0 is the announcement day, weighted by the market capitalization of both the acquirer and the target. I measure the lottery-like feature for the acquirer and the target using the average top three monthly returns from the past year before the month of the announcement (Max3). Combined_Max3 is the average Max3, weighted by the market capitalization of the acquirer and the target. CoMax3 is the percentage of top returns that occur in the same month for both the acquire and the target. The idea of lottery-like acquirer and target hitting "jackpots" together is captured by Combined_Max3×CoMax3. Detailed description of all independent variables can be found in the appendix. All independent variables are standardized to have a standard deviation of one. I estimate time-fixed effect panel regressions with standard errors (reported in brackets) clustered by time. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: Combined CAR [−1,+1]			
VARIABLES	(1)	(2)	(3)	(4)
Combined_Max3	-0.990*	-1.280**	-1.268**	-1.729***
	(0.513)	(0.571)	(0.542)	(0.570)
CoMax3			0.323	0.256
			(0.211)	(0.207)
Combined_Max3×CoMax3			0.624***	0.744***
			(0.189)	(0.186)
Disagreement		-0.0108		-0.0320
		(0.340)		(0.343)
Ln(Acq_MktCap)		-0.894*		-0.902*
		(0.450)		(0.465)
Ln(Acq_MEBE)		-0.0126		0.00748
		(0.352)		(0.353)
Acq_RoA		0.157		0.179
		(0.509)		(0.475)
Acq_Leverage		-0.215		-0.203
		(0.327)		(0.318)
Acq_OCF		-0.284		-0.273
		(0.359)		(0.341)
Ln(Tgt_MktCap)		0.320		0.286
		(0.368)		(0.383)
Ln(Tgt_MEBE)		-0.586**		-0.546**
		(0.246)		(0.247)
Tgt_RoA		-0.0393		-0.0427
		(0.476)		(0.474)
Tgt_Leverage		0.385		0.351
		(0.226)		(0.231)
Tgt_OCF		-0.0110		0.00358
		(0.476)		(0.474)
Relative Size		-0.987**		-0.996**
		(0.395)		(0.385)
Tender Offer		0.164		0.169
		(0.207)		(0.204)

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	Dependent Variable: Combined CAR [−1,+1]			
VARIABLES	(1)	(2)	(3)	(4)
Hostile Offer		0.389		0.373
		(0.241)		(0.233)
Competing Offer		-0.0776		-0.0426
		(0.202)		(0.191)
Cash Only		1.330***		1.288***
		(0.206)		(0.204)
Stock Only		-0.0306		-0.0712
		(0.295)		(0.294)
Same Industry		0.148		0.0984
		(0.170)		(0.181)
Combined_Tskew		-0.173		-0.151
		(0.174)		(0.173)
Combined_Ivol_Rank		0.356		0.497
		(0.295)		(0.308)
Fixed Effect	Time	Time	Time	Time
Observations	1,145	1,145	1,145	1,145
R-squared	0.078	0.174	0.087	0.184

Table 5 Conglomerate Firm Premium/Discount

This table reports coefficient estimates from regressions of annual conglomerate premium on measures of lotter-like features. The dependent variable is the difference between the conglomerate's market-to-book ratio (MEBE) and its imputed MEBE, divided by the latter. Imputed MEBE is the sales-weighted average MEBE from each segment. I measure the lottery-like feature using the average top three monthly returns from the past year before the month of the accounting information (Max3). Ex_Max3 is the difference between a conglomerate firm's Max3 (Cong_Max3) and its imputed Max3 (Imputed_Max3). Imputed_Max3 is the sales-weighted average Max3 from each segment. For each segment a conglomerate firm operates in, I get the top five best matched single-segment firms operating within that segment. I construct CoMax3 and Pair_Max3×CoMax3 as follow: for each conglomerate firm, I first get all the segment pairs. Then, within each segment pair, I match stock pairs, one from each segment, using the top five best matched single segment firms from each segment. For each stock pair, I count the percentage of Max3 that coincides in the same month. This percentage is first weighted by sales from both stocks across pairs, and then weighted by sales across segment pairs (CoMax3). For each stock pair, the idea of lottery-like stocks hitting "jackpots" together is captured by Pair_Max3×CoMax3, where Pair_Max3 is the sales-weighted average Max3 for the pair. Both CoMax3 and Pair_Max3×CoMax3 are taken average across stock pairs, and then segment pairs. All independent variables are standardized to have a standard deviation of one. I estimate time-fixed effect panel regressions with standard errors (reported in brackets) clustered by both firm and time. *, **, and *** denote significance at 10%, 5%, 1% level, respectively.

	Dependent Variable: Conglomerate Firm Premium/Discount				
VARIABLES	(1)	(2)	(3)	(4)	(4)
Ex_Max3	0.100***	0.195***			
	(0.0184)	(0.0260)			
Imputed_Max3			-0.0922***	-0.121***	-0.163***
			(0.0212)	(0.0258)	(0.0276)
Cong_Max3			0.0974***	0.0968***	0.202***
			(0.0205)	(0.0204)	(0.0280)
Pair_Max3×CoMax3				0.0565**	0.0737***
				(0.0248)	(0.0237)
CoMax3				-0.0421*	-0.0454**
				(0.0230)	(0.0213)
Disagreement		-0.00882			-0.00793
		(0.0184)			(0.0179)
Ln(Total Asset)		-0.0118			-0.0179
		(0.107)			(0.108)
Ln(Total Asset2)		-0.00463			-0.00449
		(0.111)			(0.111)
Leverage		0.131***			0.130***
		(0.0239)			(0.0240)
Profitability		0.0816***			0.0799***
		(0.0216)			(0.0217)
Investment Ratio		-0.00696			-0.00518
		(0.0196)			(0.0194)
Ex_Tskew		-0.0460***			-0.0461***
		(0.0121)			(0.0122)
Ex_Ivol_Rank		-0.120***			-0.126***
		(0.0190)			(0.0189)
Fixed Effect	Time	Time	Time	Time	Time
Observations	15,907	15,907	15,907	15,907	15,907
R-squared	0.013	0.042	0.014	0.015	0.043

Table 6 Placebo Test: Replace CoMax with Return Correlation

This table conducts placebo tests by replacing CoMax with non-Max return correlation. In Panel A, I report coefficient estimates from regressions of closed-end fund (CEF) premia on measures of the lottery-like features. The dependent variable is the difference between the CEF's market price and the CEF's NAV, divided by NAV (expressed in %). Lottery-like feature is proxied by the average of the top five daily returns within the month (Max5), following Bali, Cakici, and Whitelaw (2011). Ex_Max5 is the difference between a CEF's Max5 and the weighted average Max5 of its top 10 holdings. I compute return correlations by isolating the effect of CoMax. Specifically, for each stock pair from a CEF's top ten holdings, I get the daily return series for both of them and exclude the Max returns happen at the same days. The non-Max return correlation is computed using the remaining returns(Non_Max_Corr). The interaction term becomes Pair_Max5×Non_Max_Corr, where Pair_Max5 is the weighted average MAX5 for the stock pair (Pair_Max5). Both variables are then taken average across all stock pairs. All control variables are exactly the same as in Table 3. I estimate fixed effect panel regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. In Panel B, I report coefficient estimates from regressions of combined M&A announcement day returns on measure of lottery-like features. The dependent variable is combined cumulative abnormal return (CAR [−1,+1]), where *t*=0 is the announcement day, weighted by the market capitalization of both the acquirer and the target. I measure the lottery-like feature for the acquirer and the target using the average top three monthly returns from the past year before the month of the announcement (Max3). Combined_Max3 is the average Max3, weighted by the market capitalization of the acquirer and the target. I compute return correlations by isolating the effect of CoMax. Specifically, I get the monthly return series from the past year for both the acquire and the target, and exclude the Max returns happen in the same months (Non_Max_Corr). The interaction term becomes Combined_Max3×Non_Max_Corr. All control variables are exactly the same as in Table 4. I estimate time-fixed effect panel regressions with standard errors (reported in brackets) clustered by time. In Panel C, I report coefficient estimates from regressions of annual conglomerate premium on measures of lotter-like features. The dependent variable is the difference between the conglomerate's market-to-book ratio (MEBE) and its imputed MEBE, divided by the conglomerate's imputed MEBE. Imputed MEBE is the sales-weighted average MEBE from each segment. I measure the lottery-like feature using the average top three monthly returns from the past year before the month of the accounting information (Max3). Ex_Max3 is the difference between a conglomerate firm's Max3 (Cong_Max3) and its imputed Max3 (Imputed_Max3). I compute return correlations by isolating the effect of CoMax. Specifically, for each stock pair within each segment pair, I get the monthly return series from the past year for both stocks, and exclude the Max returns happen at the same months. The return correlation is computed using the remaining monthly returns (Non_Max_Corr). The interaction term is captured at pair level as Pair_Max3×Non_Max_Corr, where Pair_Max3 is the weighted average Max3 of the two stocks in the pair. Both Non_Max_Corr and the interaction term are taken average across stock pairs, and then across segment pairs. All control variables are exactly the same as in Table 5. I estimate time-fixed effect panel regressions with standard errors (reported in brackets) clustered by both firm and time. Detailed description of all independent variables from both panels can be found in the appendix. All independent variables in both panels are standardized to have a standard deviation of one. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Closed-end Fund

	Dependent Variable: CEF Premium		
VARIABLES	(1)	(2)	(3)
Holding_Max5	-7.463***	-1.767**	-1.331***
	(2.384)	(0.877)	(0.500)
CEF_Max5	6.940***	1.731***	1.614***
	(1.728)	(0.574)	(0.478)
Pair_Max5×Non_Max_Corr	0.411	0.109	0.0932
	(0.492)	(0.345)	(0.129)
Corr	-0.225	-0.598	-0.426*
	(0.910)	(0.455)	(0.229)
Controls	No	Yes	Yes
Fixed Effect	Time	Time	Fund, Time
Observations	2,330	2,330	2,330
R-squared	0.212	0.676	0.840

(Continued)

Panel B: Mergers and Acquisitions

	Dependent Variable: Combined CAR[-1,+1]	
VARIABLES	(1)	(2)
Combined_Max3	-1.036*	-1.418**
	(0.505)	(0.522)
Corr	0.221	0.251
	(0.218)	(0.205)
Combined_Max3×Non_Max_Corr	0.126	0.238
	(0.255)	(0.253)
Controls	No	Yes
Fixed Effect	Time	Time
Observations	1,145	1,145
R-squared	0.079	0.176

Panel C: Conglomerate Firms

	Dependent Variable: Conglomerate Firm Premium/Discount	
VARIABLES	(1)	(2)
Imputed_Max3	-0.0849***	-0.119***
	(0.0211)	(0.0218)
Cong_Max3	0.0985***	0.200***
	(0.0203)	(0.0278)
Pair_Max3×Non_Max_Corr	-0.0584*	-0.0320
	(0.0339)	(0.0300)
Corr	0.0250	0.00910
	(0.0308)	(0.0264)
Controls	No	Yes
Fixed Effect	Time	Time
Observations	15,907	15,907
R-squared	0.015	0.042

Table 7 The Effect of Lottery-like Feature on CEF Inceptions and the Likelihood of Mergers and Acquisitions

This table examine the effect of lottery-like features on CEF inceptions and the likelihood of mergers and acquisitions. Panel A reports coefficient estimates from logit regressions of CEFs' actual and potential holding pairs at inception on the pairs' lottery-like features. For each top ten holding at the CEF inception, I search for ten potential holdings based on propensity-score matching by reference to size, book-to-market ratio, and past returns. These pseudo holdings are similar to the actual holdings but are not selected into the CEF portfolio. Therefore, each CEF should have 45 actual pairs from top-ten holdings, and 4500 pseudo pairs from potential holdings. I pool all the potential pairs together with the actual pairs for the regressions. The dependent variable equals one for the actual pairs, and zero otherwise. Lottery-like feature is proxied by the average of the top five daily returns within the month (Max5), following Bali, Cakici, and Whitelaw (2011). For each stock pair, Pair_Max5 is the weighted average MAX5 of the two stocks, while CoMax5 is defined as the percentage of the top five daily returns from the two stocks that occur at the same time. The idea of lottery-like stocks hitting "jackpots" together is captured by Pair_Max5×CoMax5. Time fixed effects are included and standard errors are clustered by time (reported in parentheses). Panel B reports coefficient estimates from logit regressions of actual and potential M&A deals on measures of lottery-like features. In columns (1) and (2), I search ten potential targets for each actual acquirer in each M&A, based on propensity-score matching by reference to two-digit SIC code and various firm characteristics. These potential targets are similar to the actual target but are not involved in the M&A. The sample is further divided into two groups: acquirers with low lottery-feature (column 1) and acquirers with high lottery-feature (column 2). Similarly, in columns (3) and (4), I search ten potential acquirers for each actual target in each M&A, based on propensity-score matching by reference to two-digit SIC code and various firm characteristics. These potential acquirers are similar to the actual acquirer but are not involved in the M&A. The sample is further divided into two groups: targets with low lottery-feature (column 3) and targets with high lottery-feature (column 4). In column 5, I combine the two practices by searching both potential acquirers and potential targets based on the same requirements. I pool all the potential acquirer-target pairs together with the actual acquirer-target pair in each setting. The dependent variable equals one for the actual M&A, and zero otherwise. I measure the lottery-like feature for the acquirer and the target using the average top three monthly returns from the past year before the month of the announcement (Max3). Combined_Max3 is the average Max3, weighted by the market capitalization of the acquirer and the target. CoMax3 is the percentage of top returns that occur in the same month for both the acquire and the target. The idea of lottery-like acquirer and target hitting "jackpots" together is captured by Combined_Max3×CoMax3. Time fixed effects are included and standard errors are clustered by time (reported in parentheses). All variables in both panels are standardized to have a standard deviation of one. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: CEF Inceptions		
	Pseudo Holdings	
VARIABLES	(1)	(2)
Pair_Max5	-0.239***	-0.162***
	(0.0350)	(0.0626)
CoMax5		0.249***
		(0.0653)
Pair_Max5×CoMax5		-0.120
		(0.0836)
Stock Characteristics	Yes	Yes
No.Obs	172,710	172,710

(Continued)

(Continued)

Panel B: Likelihood of Mergers and Acquisitions					
	Pseudo Target Only		Pseudo Acquirer Only		Pseudo Acquirer and Pseudo Target
	Acq with low MAX3	Acq with high MAX3	Tgt with low MAX3	Tgt with high MAX3	
VARIABLES	(1)	(2)	(3)	(4)	(5)
Combined_Max3	-0.164	-0.147	-0.0874	-0.0833	-0.0901
	(0.228)	(0.0981)	(0.172)	(0.0694)	(0.0705)
CoMax3	0.140	-0.129	-0.0158	-0.0380	0.0294
	(0.165)	(0.127)	(0.125)	(0.0782)	(0.0773)
Combined_Max3×CoMax3	0.00265	0.288**	0.237	0.183**	0.166**
	(0.319)	(0.116)	(0.215)	(0.0774)	(0.0802)
Acquirer Characteristics	Yes	Yes	Yes	Yes	Yes
Target Characteristics	Yes	Yes	Yes	Yes	Yes
Relative Size	Yes	Yes	Yes	Yes	Yes
Observations	4,565	4,565	4,653	4,653	77,319