Diversification in Lottery-Like Features and Portfolio Pricing Discounts*

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Abstract

I study the asset pricing implications of cumulative prospect theory on portfolio discounts. I extend Barberis and Huang (2008) and show that a portfolio consisting of lottery-like stocks should trade at a discount due to diversification. This discount can be partially mitigated if lottery-like stocks tend to produce extreme payoffs at the same time. I utilize three empirical settings to support this theoretical prediction: the closed-end fund puzzle, the announcement returns of mergers and acquisitions, and conglomerate discounts. My findings support cumulative prospect theory from an alternative perspective and provide a novel and unifying explanation for three seemingly unrelated phenomena.

Keywords: Cumulative Prospect Theory, *CoMax*, Diversification, Lottery-like Feature, Discount

JEL Classification: G11, G12, G41

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1 Introduction

A central research question for economists and psychologists is how investors behave under uncertainty. Most of the existing theories are based on the assumption that investors evaluate uncertainty according to the expected utility framework. However, a large body of experimental evidence has shown that people usually depart significantly from the predictions of expected utility when making risky decisions. By contrast, cumulative prospect theory (Tversky and Kahneman, 1992) can capture these behaviors, and can help understand puzzling asset pricing patterns from the financial market.

Previous research on the pricing implications of prospect theory has mainly focused on the shape of the value function (e.g., Benartzi and Thaler, 1995; Barberis, Huang, and Santos, 2001; Barberis and Xiong, 2009; Li and Yang, 2013; An, 2015; Easley and Yang, 2015), or the negative expected returns from lottery-like (i.e., positively skewed) stocks (e.g., Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011; Barberis, Mukherjee, and Wang, 2016; An, Wang, Wang, and Yu, 2019). Here, I focus on a less-studied aspect: portfolio discounts. Specifically, I examine a new theoretical prediction concerning portfolio prices under cumulative prospect theory, and I test this prediction on closed-end fund (CEFs) discounts, combined announcement returns from mergers and acquisitions (M&A), and conglomerate discounts.[1]

[1] "Closed-end fund discount" refers to the phenomenon that closed-end fund shares are typically traded at prices lower than the per share market value of its underlying assets (e.g., Lee, Shleifer and Thaler, 1991; Chen, Kan, and Miller, 1993; Pontiff, 1996;

First, I extend cumulative prospect theory in a portfolio setting and show that, a portfolio consisting of lottery-like stocks should trade at a discount. This extension is based on Barberis and Huang (2008), who argue that, in an economy with cumulative prospect theory investors, a lottery-like stock can become overpriced because investors overweight the small probability of a large payoff. I extend their model to examine multiple lottery-like stocks. These stocks can provide extreme positive payoffs with a small probability, but not necessarily at the same time. I analyze the asset pricing implication from this extended model by comparing two economies. In the first economy, investors can trade lottery-like stocks on their own. In the second economy, investors can only trade a portfolio consisting of these lottery-like stocks. I find that the portfolio price in the second economy is lower than the prices of lottery-like stocks in the first economy (the difference is referred as the portfolio pricing discount hereafter). More importantly, this discount depends on how likely the lottery-like stocks produce extreme payoffs at the same time. Specifically, when the stocks are more likely to produce extreme payoffs at the same time, the portfolio pricing discount is smaller.

The intuition behind this theoretical prediction is based on cumulative prospect theory and the diversification in lottery-like features. Consider the following two cases. In the first case, the

Hwang, 2011; Wu, Wermers, and Zechner, 2016; Hwang and Kim, 2017). Existing literature has shown that M&As often have negative combined announcement returns from acquirers and targets (e.g., Morck, Shleifer, and Vishny, 1990; Moeller, Schlingemann, and Stulz, 2005; Masulis, Wang, and Xie, 2007; Cai and Sevilir, 2012). "Conglomerate discount" refers to the empirical fact that a conglomerate is usually worth less than a portfolio of comparable single-segment firms in terms of market-to-book ratio (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995; Servaes, 1996; Lamont and Polk, 2001; Laeven and Levine, 2007; Hund, Monk, and Tice, 2010). These phenomena are puzzling and are suggestive evidence for market inefficiency.

lottery-like stocks have a low tendency of producing extreme payoffs together. When they are combined into a portfolio (e.g., a closed-end fund), the return distribution of this portfolio will become less lottery-like than each individual stock due to diversification. Under cumulative prospect theory, investors overweight small probabilities, and therefore exhibit a preference for lottery-like payoffs. Since the portfolio becomes less attractive to investors, it will trade at a lower price. On the other hand, when investors trade lottery-like stocks alone, the lottery-like feature makes them attractive and they will be traded at a higher price. Therefore, due to the diversification effect in lottery-like features, the portfolio will trade at a discount relative to its underlying stocks. Contrast this to a second case, in which lottery-like stocks always produce extreme payoffs together. In this case, when these stocks are combined into a portfolio, the portfolio obtains the same lottery-like feature. Investors will find the portfolio as attractive as its holdings and there will be no discount.

Second, I test this new theoretical prediction using three empirical settings: CEFs, M&As, and conglomerates. I use CEFs as my main setting for the following reasons. First, a large body of literature has documented that a CEF is typically traded at a discount relative to the market value of its underlying assets. This discount has been a long-standing puzzle among academics and practitioners. Second, CEFs provide a clean setting to control for firm characteristics. Since stocks are combined and traded as a portfolio, the difference in value between a portfolio and the sum of its holdings should not be affected by firm characteristics, particularly those that are potentially correlated with lottery-like features.[2] Utilizing this advantage, CEFs provide a relatively clean and powerful approach to test the relevance of prospect theory and lottery-like features in determining asset prices by directly comparing the market price of the portfolio with its intrinsic value (i.e., the market value of its underlying stocks).

In my empirical tests, I assume that when a typical CEF investor evaluates the holdings from a CEF, such an investor is more likely to look at a fund's top-10 holdings. The average CEF in my sample holds around a hundred stocks. Obtaining the full holdings requires investors to go through a fund's annual report, and it is impossible to keep all of them in mind. On the contrary, top-10 holdings are readily observable from a fund's website, factsheets, and financial media (such as Morningstar, Yahoo! Finance, etc.). They account for a substantial portion of the total portfolio value and represent the investment objectives of the fund. Therefore, focusing on top-10 holdings from each CEF is reasonable for investors when they evaluate a CEF, especially for retail investors, who are the primary investors for CEFs. Indeed, according to a survey by Huang, Hwang, Lou, and Yin (2019), almost all investors evaluate CEFs through sources which prominently display a fund's top-ten holdings.[3]

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

[3] Huang, Hwang, Lou, and Yin (2019) argues that investor disagreement and belief crossing can generate a wedge in valuation between the portfolio and the sum of its components. In my main results, I have controlled for analysts' forecast dispersion and idiosyncratic volatility as proxies for investor disagreement. In untabulated tests, I have also followed their paper to include belief crossing and its interaction with disagreement into the regressions. My results remain qualitatively similar.

To empirically test the model prediction, I follow Bali, Cakici, and Whitelaw (2011) and use the average top-5 daily returns within a month to proxy for the lottery-like feature (denoted as $Max(5)$).[4] A high $Max(5)$ represents a large investment return, which directly captures the low probability and extreme payoff state that drives the pricing implication in cumulative prospect theory. Since investors mainly focus on top-10 holdings, I compute the overall lottery-like feature from a CEF's holdings as the average $Max(5)$ from the top-10 holdings, weighted by their respective portfolio weights (denoted as $Holding\_Max(5)$). A high $Holding\_Max(5)$ indicates a strong lottery-like feature from a CEF's holdings.

To directly show the diversification effect in lottery-like features among the top-10 holdings, I construct a proxy, $CoMax$, to capture the tendency for lottery-like payoffs to be produced at the same time. Specifically, for every possible stock pair $\{i, j\}$ within a CEF's top-10 holdings, I compute the percentage of the top-5 daily returns that are recorded in the same day, and denote it as $CoMax(5)_{i,j}$, where $CoMax(5)_{i,j} \in [0,1]$. The lottery-like feature of each stock pair, $Pair\_Max(5)_{i,j}$, is the average $Max(5)$ from the two stocks, weighted by their portfolio weights. Therefore, $Pair\_Max(5)_{i,j} \times CoMax(5)_{i,j}$ provides useful information about both the lottery-like feature and the tendency of the stocks in each pair to pay out "jackpots" at the same time.

[4] Similar results can be obtained using top-*i* daily returns within a month as well (i = 2,3,4). I use $Max(5)$ for the main results to allow for more variation when I construct the variable to capture the tendency for lottery-like payoffs to be produced at the same time. Similar results can also be obtained by using extreme returns within a year. These additional results are reported in Table 6.

These variables are further integrated at the fund level based on holding weights (denoted as $CoMax(5)$, $Holding\_Max(5)$, and $Pair\_Max(5) \times CoMax(5)$).[5]

Consistent with the theoretical prediction, my empirical results show that a strong lottery-like feature from a CEF's holdings leads to a high CEF discount. My panel regression of CEF discount on $Holding\_Max(5)$, $Pair\_Max(5) \times CoMax(5)$, and a host of controls produces an estimate for $Holding\_Max(5)$ of 1.94, suggesting that a one-standard-deviation increase in $Holding\_Max(5)$ comes with a 1.94% increase in the CEF discount (t-statistic = 4.33). Considering that the average CEF discount in my sample is 4.70%, this effect is not only statistically significant but also economically large. On the other hand, if a CEF's holdings have strong lottery-like features and a high $CoMax(5)$, the discount on the CEF price can be partially mitigated. A one-standard-deviation increase in $Pair\_Max(5) \times CoMax(5)$ can help offset the CEF discount by 0.49% (t-statistic = 3.97).[6]

An alternative proxy to capture the diversification in lottery-like features is to compare the difference in $Max(5)$ from a CEF (denoted as $CEF\_Max(5)$) and $Holding\_Max(5)$. However, this is a noisy and indirect measure. First, in reality, CEFs can hold a very diversified portfolio consisting of equities, bonds, derivatives, and other securities in the US and in other countries.

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[5] Note that when $Pair\_Max(5)_{i,j}$ is taken as a weighted average across all stock pairs, it becomes $Holding\_Max(5)$ because every stock is counted twice.

[6] Further analyses show that the variation of limits-to-arbitrage has an impact on this effect. Specifically, my results are stronger (1) during periods when funding costs for arbitrageurs are high; (2) for CEFs with low average institutional ownership from holding stocks. For brevity, these results are available upon requests.

Price movements from all other assets may affect CEF returns. Second, it has been well documented that CEF prices can be affected by various factors, such as investor sentiment. Finally, this is an aggregated and indirect measure, while $CoMax$ directly captures how lottery-like features are diversified away among top-10 holdings. Based on these reasons, I compute $CoMax(5)$, which does not rely on the CEF itself, to mitigate potential noises and provide direct evidence on the mechanism. That being said, using the difference between $CEF\_Max(5)$ and $Holding\_Max(5)$, or controlling $CEF\_Max(5)$ in all regressions can produce similar results.

I extend my empirical tests to incorporate M&As and find similar results. In an M&A deal, the new joint firm can be regarded as a "portfolio" which has two "underlying stocks": the acquirer and the target. The combined announcement return from both the acquirer and the target (denoted as $Combined\_CAR[-1,+1]$) can proxy for the difference between the value of the "portfolio" (the new joint firm) and the total value of its "underlying assets" (the acquirer and the target as two separate firms) shortly after the news announcement. Similar to CEFs, the diversification in lottery-like features can help explain the combined announcement returns from M&As.

As my final setting, a conglomerate can be regarded as a "portfolio" consisting of different business segments. Prior literature has shown that a conglomerate usually has a low market-to-book ratio compared to its single-segment counterparts. Consistent with the previous two settings, I find that the diversification in lottery-like features can help explain the low market-to-book ratio of conglomerates.

A potential concern from these three sets of results is that $CoMax$ simply captures return correlation. To address this concern, I conduct placebo tests by replacing $CoMax$ with a return correlation constructed after excluding concurrent extreme returns.[7] In all three sets of placebo tests, the interactions between the return correlation and the lottery-like feature become insignificant. These placebo tests further confirm that diversification in lottery-like features, not return correlation, contributes to the portfolio pricing discount.

My paper contributes to the literature as follows. First, I extend cumulative prospect theory in a portfolio setting with multiple lottery-like stocks. Existing studies on the pricing implications of prospect theory has mainly focused on the implications of the kink in the value function (e.g., Benartzi and Thaler, 1995; Barberis, Huang, and Santos, 2001; Easley and Yang, 2015), the implications of the convex/concave portion of the value function (e.g., Frazzini, 2006; Barberis and Xiong, 2009; Li and Yang, 2013; An, 2015), or testing the theoretical prediction on the negative expected returns for lottery-like stocks (e.g., Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011; Barberis, Mukherjee, and Wang, 2016; An, Wang, Wang, and Yu, 2019). Taking a different approach, my paper focuses on a novel and less-studied perspective: portfolio discounts. I show that, under cumulative prospect theory, when investors trade a portfolio

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[7] Section 5.1 provides more details on how this return correlation is constructed. It requires excluding the concurrent extreme returns to avoid a mechanical relation between $CoMax$ and correlation.

consisting of lottery-like stocks, the portfolio should trade at a discount. This discount depends on how likely these lottery-like holdings are to produce extreme payoffs at the same time.

Empirically, my paper extends cumulative prospect theory to new territories to understand puzzling phenomena in the financial market. I utilize CEFs, M&As, and conglomerates to test my theoretical predictions and find consistent results. These empirical findings not only support prospect theory from a new perspective, but also provide a novel and unifying framework for three seemingly unrelated phenomena, i.e., the closed-end fund puzzle, the combined announcement return of a M&A deal, and the conglomerate discount.

2 The Model

2.1 Model Setup

Following Barberis and Huang (2008), I consider a one-period economy with two dates, $t = 0$ and $t = 1$. In this economy, investors use cumulative prospect theory to evaluate risk. For each investor, suppose their wealth at $t = 0$ is W_0. They invest their wealth into the stock market and earn a gross return of r. Thus, their final wealth at $t = 1$ becomes $W_1 = W_0 r$. Assume the economy contains a risk-free asset, which is in perfectly elastic supply and has a gross return of r_f. The investor chooses $W_0 r_f$ as their reference point. The gain (loss) the investor gets from $t = 1$ is defined as:

$$x = W_0 r - W_0 r_f \tag{1}$$

The investor has the following value function:

$$v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x < 0 \end{cases}. \tag{2}$$

The coefficient of loss aversion, λ, determines the degree of sensitivity to losses. For $\alpha \in (0,1)$, $\beta \in (0,1)$, and $\lambda > 1$, this value function is concave over gains, convex over losses, and exhibits a greater sensitivity to losses than to gains.

The investor applies probability weighting functions to the cumulative probability distribution of gains and losses. Specifically, the functional forms are:

$$w^{+}(P) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{\frac{1}{\gamma}}}, w^{-}(P) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{\frac{1}{\delta}}}, \tag{3}$$

where w^{+} and w^{-} are the probability weighting functions for gains and losses, respectively. P is the cumulative probability distribution function. For $\gamma \in (0,1)$ and $\delta \in (0,1)$, the investor overweights small probabilities, i.e., for small and positive P, $w(P) > P$. In other words, the investor exhibits a preference for lottery-like payoffs.

The goal function for this investor is:

$$U(W_1) \equiv V(x) = V(x^{+}) + V(x^{-}) \tag{4}$$

where $x^{+} = \max\ (x, 0)$, and $x^{-} = \min\ (x, 0)$, and

$$V(x^{+}) = -\int_{0}^{\infty} v(x) dw^{+}\big(1 - P(x)\big) = \int_{0}^{\infty} w^{+}\big(1 - P(x)\big)\, dv(x) \tag{5}$$

$$V(x^{-}) = \int_{-\infty}^{0} v(x) dw^{-}\big(P(x)\big) = -\int_{-\infty}^{0} w^{-}(P(x))\, dv(x) \tag{6}$$

Assume the economy has a market portfolio and two lottery-like stocks. Investors choose to allocate ϕ to the lottery-like stocks relative to the amount allocated to the market portfolio. The excess return on the market portfolio, excluding the lottery-like stocks, is normally distributed: $r_m \sim N(\mu_m, \sigma_m^2)$. Each of the lottery-like stocks follows a binomial distribution: with a low probability v, the security pays out a large "jackpot" J, and with probability $1 - v$, it pays out nothing. For a very large J and a very small v, this binomial distribution resembles a lottery ticket. The returns on the lottery-like stocks are independent of the market portfolio, and the payoffs from the lottery-like stocks are infinitesimal relative to the total payoff from the market portfolio. Since the two lottery-like stocks are identical, they must be priced equally in the equilibrium. I denote this price as p_l, and the excess return of the lottery-like stocks, $r_{l,i}$ ($i =$ 1 or 2), is distributed as $r_{l,i} \sim (J/p_l - r_f, v;\ -r_f, 1 - v)$.

Based on Barberis and Huang (2008), this economy has an equilibrium with three global optima: a portfolio that combines the risk-free asset, the market portfolio, and a positive $\phi^* > 0$ in just the first (second) lottery-like stock; and a portfolio that holds only the risk-free asset and the market portfolio. Provided $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$, the equilibrium price for the two lottery-like stocks and the holding weight should be $(p_l, \phi^*) = (0.925, 0.085)$. I consider this economy as a benchmark. The equilibrium price for the lottery-like stocks in this economy will be carried out to define the portfolio pricing discount that I will introduce in a second economy in Section 2.2.

2.2 Portfolio Pricing

Consider a second economy. It is identical to the benchmark economy described in Section 2.1, except that investors can no longer trade the two lottery-like stocks directly. Instead, they can trade a portfolio which invests equally in the two lottery-like stocks. The excess return of the portfolio depends on the probability that both lottery-like stocks pay out "jackpots" at the same time. I denote:

Joint Probability		Lottery-like Stock 2	
		$Payoff = J$	$Payoff = 0$
Lottery-like Stock 1	$Payoff = J$	u	$v-u$
	$Payoff = 0$	$v-u$	$1-2v+u$

I define $CoMax = u/v$, and the excess return of the portfolio, r_s, is distributed as:

$$r_s \sim \left(\frac{J}{p_s} - r_f, u;\ \frac{J}{2p_s} - r_f, 2v-2u;\ -r_f, 1-2v+u\right). \tag{7}$$

where p_s is the market price of the portfolio.

In this new economy, two types of equilibria may exist, depending on parameters. A homogeneous holdings equilibrium is an equilibrium in which all investors hold the same position.

In this equilibrium, each investor will hold an infinitesimal amount ε^* of the portfolio. The price of the portfolio, p_s, does not depend on u:[8]

$$p_s = \frac{vJ}{r_f} \ . \tag{8}$$

The other type of equilibrium is a heterogenous holdings equilibrium with two groups of investors (these investors are ex-ante homogeneous), where the first group holds a combination of the risk-free asset, the market portfolio, and the new portfolio; and the second group holds the risk-free asset and the market portfolio but takes no position in the new portfolio. Markets are cleared by assigning each investor to one of the optima. The portfolio price does not have an analytical solution. It depends not only on the lottery-like feature from its holdings (v), but also on the probability that both lottery-like stocks pay out "jackpots" at the same time $(CoMax)$. Detailed descriptions for the conditions of these two types of equilibria are provided in Appendix 2.

2.3 An Example

I solve the equilibrium price of the portfolio for different levels of $CoMax$ numerically under the same set of parameters adopted in the benchmark economy. I start from a special case: when $CoMax = 1$ (i.e., $u = v$), the portfolio should be priced at 0.925, i.e., the price of the two lottery-like stocks from the benchmark economy. No discount is observed. However, as $CoMax$ decreases, the lottery-like feature of the portfolio drops while the expected payoff of the portfolio

[8] See Proposition 2 in Barberis and Huang (2008)

remains the same. Since investors only value the tails of their wealth distribution, the portfolio becomes less attractive and should be traded at a lower price.

For example, when $u = 0.08$, a heterogenous holdings equilibrium can exist. The red line from Figure 1a provides a graphical illustration of the value function. At $p_s = 0.922$, the value function produces two global optima at $\phi = 0$ and $\phi^* = 0.088$, where ϕ is the amount allocated to the new portfolio relative to the amount allocated to the market portfolio. The market is cleared by assigning each investor to one of the two global optima.

[Figure 1 Here]

The intuition of the heterogenous holdings equilibrium is as follows. When investors hold a small position in the new portfolio relative to their position in the market portfolio, their utility drops because the portfolio has a negative expected return ($E(r_s) = vJ/p_s - r_f = -4.39\%$). As the position on the portfolio increases, investors' wealth distributions start to have significant lottery-like features. This increases investors' utility under prospect theory because they overweight small probabilities and value lottery-like payoffs. At a price level of $p_s = 0.922$, the benefit of adding lottery-like features to investors' wealth distributions offsets the negative excess return from holding the portfolio, producing both $\phi = 0$ and $\phi^* = 0.088$ as global optima.

Compared to the price of the lottery-like stocks in the benchmark economy, the portfolio is now traded at a 0.32% discount ($1 - 0.922/0.925$). The lesson from this example is that, when

$CoMax < 1$, the portfolio starts to trade at a lower price relative to its underlying assets. However, since $CoMax$ is still reasonably high, this discount is very small.

For these parameter values, there exists no equilibrium in which all investors with access to the portfolio hold the same position. According to (8), in a homogeneous holdings equilibrium, $p_s = 0.882$. The blue line in Figure 1a shows that $p_s = 0.882$ does not support an equilibrium, because all investors would prefer a substantial positive position in the portfolio to an infinitesimal one, making it impossible to clear the market.

However, when $CoMax$ is low, a homogeneous holdings equilibrium can exist. In Figure 1b, the blue line shows that, when $u = 0.01$, $\phi^* = \varepsilon^* \to 0$ is not only a local optimum but also a global optimum. Therefore, all investors would prefer to hold an infinitesimal positive position, and the portfolio is traded at $p_s = 0.882$, or in other words, a 4.65% discount. This discount is a lot higher compared to the case when $u = 0.08$, because $CoMax$ is very low.

The intuition for the homogenous holdings equilibrium is that, when $CoMax$ is low, the portfolio does not have a sufficient lottery-like feature anymore. Therefore, any investment in this portfolio cannot add enough lottery-like feature to an investor's wealth distribution to compensate for the negative expected returns received from holding the portfolio. Since investors only overweight the right-tail of the distribution, cumulative prospect theory assigns the portfolio the same expected return that a concave expected utility theory would assign, i.e., $E(r_s) = 0$.

For these parameter values, a heterogeneous holdings equilibrium is not feasible. The red line in Figure 1b suggests that the utility becomes positive for a small $\phi > 0$. Therefore, all investors would prefer a positive position in the portfolio, making it impossible to clear the market.

For different levels of $CoMax$, I search for the portfolio price that satisfies a heterogenous holdings equilibrium first, and if it does not exist, I switch to search for the price in a homogeneous holdings equilibrium. I plot the relation between $CoMax$ and the portfolio discount in Figure 2.

[Figure 2 Here]

Figure 2 shows that, holding v constant, the model predicts a negative relation between $CoMax$ and the portfolio discount. When $CoMax$ decreases, the lottery-like feature of the portfolio declines. This negatively affects the price of the portfolio, making the portfolio trade at an increasing discount. As $CoMax$ drops below 0.40, the portfolio cannot offer enough of a lottery-like feature to support a heterogeneous holdings equilibrium, and cumulative prospect theory assigns a price $p_s < p_l$ regardless of $CoMax$.

2.4 v, $CoMax$, and Portfolio Discount

In Figure 3a, I plot the portfolio discount as a function of $CoMax$ for $v = 0.09$ (red line), $v = 0.07$ (blue line), and $v = 0.05$ (green line). In all three cases, a low $CoMax$ leads to a high portfolio discount. Provided the same level of $CoMax$, the discount on the portfolio is severe when v is low, i.e., when the portfolio holds stocks with strong lottery-like features. On the other hand, when v is high, the effect of $CoMax$ on the portfolio price is weak.

[Figure 3 Here]

In Figure 3b, I plot the portfolio discount as a function of v for $CoMax = 1.0$ (red line), $CoMax = 0.7$ (blue line), $CoMax = 0.4$ (green line), and $CoMax = 0.1$ (purple line). When $CoMax = 1.0$ (no diversification), the portfolio is always traded at a price equal to the lottery-like stocks regardless of v. In the other three cases, a low v leads to a high portfolio discount. Provided the same level of v, the discount on the portfolio is severe when $CoMax$ is low, i.e., when the two lottery-like stocks do not tend to pay off "jackpots" at the same time. On the other hand, if the two lottery-like stocks have a high $CoMax$, the discount can be partially mitigated.

Therefore, the model predicts an interaction effect: a portfolio pricing discount appears when the portfolio holds stocks with strong lottery-like features that do not tend to pay off "jackpots" at the same time.

3 Data and Variables

In this section, I introduce samples and variables to test the model prediction in three different settings: CEFs (Section 3.1), M&A (Section 3.2), and conglomerates (Section 3.3).

3.1 Closed-end Funds

My main empirical tests focus on US equity closed-end funds.[9] A CEF is a type of publicly traded mutual fund which invests in other publicly traded securities. This makes it possible to compare the market value of the fund with the total market value of its underlying assets.

Following existing literature, I first extract a list of CEFs and their monthly prices from The Center for Research in Security Prices (CRSP) by selecting securities with share codes 14 and 44. The net asset value (NAV), i.e., the total market value of a fund's underlying assets on a per-share basis, is from Compustat. The dependent variable is the CEF discount, which is defined as the difference between the a CEF's NAV and its price, divided by its NAV:

$$Discount_{i,t} = \frac{NAV_{i,t} - Price_{i,t}}{NAV_{i,t}} \quad . \tag{9}$$

For example, a CEF traded at \$4.9 but with a NAV of \$5 is described to have a discount of 2%, or in other words, a premium of −2%. To avoid any unnecessary confusion, in this paper, I always describe results in terms of discounts hereafter, following the common convention and the fact that the majority of CEFs trade at discounts. I follow standard literature to exclude data (1) within the first six months after a fund's IPO; and (2) in the month preceding the announcement of liquidation or open-ending (Chan, Jain, and Xia, 2008).[10] I obtain CEFs' holdings from Morningstar.

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9 A CEF is defined as a US equity CEF if at least 50% of its weight is invested in stocks listed in US stock exchanges.

10 These exclusions do not affect my results.

In my empirical tests, I assume that when a typical CEF investor evaluates the holdings from a CEF, such an investor is more likely to look at a fund's top-10 holdings. The average CEF in my sample holds around a hundred stocks. Obtaining the full holdings requires investors to go through a fund's annual report, and it is impossible to keep all of them in mind. On the contrary, top-10 holdings are readily observable from a fund's website, factsheets, and financial media (such as Morningstar, Yahoo! Finance, etc.). They account for a substantial portion of the total portfolio value and represent the investment objectives of the fund. Therefore, focusing on top-10 holdings from each CEF is reasonable for investors when they evaluate a CEF, especially for retail investors, who are the primary investors for CEFs. Indeed, according to a survey by Huang, Hwang, Lou, and Yin (2019), almost all investors evaluate CEFs through sources which prominently display a fund's top-ten holdings.

Another reason for focusing on the top-10 holdings is that top-10 holdings are very persistent. In the model I described in Section 2, the holdings for the portfolio does not change over time. In my sample, most of the CEFs report their holdings on a quarterly basis. Therefore, when analyzing the monthly discounts between two quarterly reports, I implicitly assume that holdings do not change within the quarter. However, portfolio rebalancing within the quarter (not observable from the holding report) can affect prices and returns for both the CEF and its holdings. Because top-10 holdings are very persistent, they do not change very much over time. Therefore, focusing on the top-10 holdings can capture the theory better and can reduce potential noise introduced by portfolio rebalancing. Indeed, in my sample, top-10 holdings from a fund report have a 95% (80%) of chance of staying the fund (top-10) in the next fund report.

The lottery-like feature is proxied by the average top-5 daily returns within a month (denoted as $Max(5)$), following Bali, Cakici, and Whitelaw (2011). In other words, around the top 25% of the returns in a month are used to capture the right-tail of the return distribution. I will keep this top 25% rule to capture the right-tail in the other two settings and in robustness checks. Similar results can be obtained using top-*i* daily returns within a month as well (i = 2,3,4). I use $Max(5)$ for the main results to allow for more variation when I construct $CoMax$. Similar results can also be obtained if I construct the variable on an annual basis. In robustness checks, I have considered using the top-60 daily return within the past year (denoted as $Max(60)$). This is a variable that will also be adopted in the robustness checks for the other two settings. Since CEF discounts can be observed on a monthly basis, it is intuitive to follow Bali, Cakici, and Whitelaw (2011) and construct a proxy for lottery-like features using daily returns from each month. On the other hand, computing $Max(60)$ in each month requires overlapping observation windows and brings unnecessary persistence to the independent variable. Therefore, $Max(5)$ is adopted for the main results. I compute the overall lottery-like feature from a CEF's holdings as the average $Max(5)$ from a CEF's top-10 holdings, weighted by their respective portfolio weights (denoted as $Holding\_Max(5)$).

To directly show the effect of the diversification in lottery-like features among holdings, I construct a proxy, $CoMax$, to capture the tendency for lottery-like payoffs to be produced at the same time. This measure is computed within the top-5 daily returns.[11] Specifically, for every possible stock pair $\{i, j\}$ within a CEF's top-10 holdings, I compute the percentage of the top-5 daily returns that are recorded in the same day, and denote it as $CoMax(5)_{i,j}$. For example, if the top-5 daily returns for Stock A come from the 1st, 4th, 9th, 11th and 15th day of the month, while the top-5 daily returns for Stock B come from the 2nd, 4th, 9th, 14th and 20th day of the month, then $CoMax(5)_{A,B}$ equals 40%. By construction, $CoMax(5)_{i,j} \in [0,1]$. For each pair of stocks $\{i, j\}$, the average lottery-like feature, $Pair\_Max(5)_{i,j}$, is the average $Max(5)$ of the two stocks, weighted by their respective portfolio weights. $Pair\_Max(5)_{i,j} \times CoMax(5)_{i,j}$ provides useful information about both the lottery-like feature and the tendency for each stock pair to pay out extreme returns at the same time. $Pair\_Max(5)_{i,j} \times CoMax(5)_{i,j}$, $Pair\_Max(5)_{i,j}$, and $CoMax(5)_{i,j}$ are further averaged across all possible stock pairs, weighted by the total portfolio weights of each stock pair (denoted as $Pair\_Max(5) \times CoMax(5)$, $Holding\_Max(5)$, and $CoMax(5)$). Note that when $Pair\_Max(5)_{i,j}$ is taken as a weighted average across all stock pairs, it becomes $Holding\_Max(5)$ because each stock is counted twice. Other versions of $CoMax$ are constructed in the same way in the robustness checks.

[11] In robustness, I also consider alternative $CoMax$ variables constructed from top-*i* daily returns (*i* = 2, 3, 60).

I follow the literature and include the following control variables that may explain CEF discounts: $CEF\_Max(5)$ (the average top-5 daily returns within a month for a CEF), disagreement (as proxied by analysts' forecast dispersion), inverse price, dividend yield, expense ratio, and liquidity ratio. In addition, I control for the weighted average skewness and idiosyncratic volatility from the top-10 holdings. Detailed descriptions of these variables can be found in the Appendix. My final sample contains 101 CEFs from 2002 to 2014. The sample period is determined by the availability of data on Morningstar.

Panel A of Table 1 reports summary statistics for the CEF sample. The average CEF discount is 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 (e.g., Lee, Shleifer and Thaler, 1991; Chen, Kan, and Miller, 1993; Bodurtha, Kim, and Lee, 1995; Pontiff, 1996; Klibanoff, Lamont, and Wizman, 1998; Chan, Jain, and Xia, 2008; Hwang, 2011; Wu, Wermers, and Zechner, 2016; Hwang and Kim, 2017).

[Table 1 Here]

The holdings exhibit stronger lottery-like features compared to the CEF itself. On average, the lottery-like feature drops about 30% when these stocks are combined into a CEF. This shows that lottery-like features indeed get diversified away at the fund level.

3.2 Mergers and Acquisitions

I extend my empirical tests to study M&As. I extract details on M&A deals from the Securities Data Corporation (SDC)'s U.S. M&A 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 the SDC dataset is more than 1 million USD.

I obtain stock returns and accounting variables from CRSP and Compustat, respectively. The dependent variable is the combined announcement return, defined as the average cumulative abnormal return over days [−1, +1] across the acquirer and the target, weighted by their market capitalizations in the month prior to the announcement:

$$Combined\_CAR[-1,+1] = w_A \times CAR_A[-1,+1] + w_T \times CAR_T[-1,+1], \qquad (10)$$

where $t = 0$ is the announcement day, or the ensuing trading day if the deal is announced when the market is closed. $CAR_A[-1,+1]$ and $CAR_T[-1,+1]$ are cumulative abnormal returns over days $[-1,+1]$ for the acquirer and the target, respectively; w_A and w_T are weights based on market capitalizations for the acquirer and the target. I use DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) to compute $CAR_A[-1,+1]$ and $CAR_T[-1,+1]$. $Combined\_CAR[-1,+1]$ captures the difference between the value of the joint firm (i.e., the "portfolio") and the total value of the acquirer and the target operating separately (i.e., the "underlying assets") around the announcement.

In the CEF setting, since CEF discounts are observed repeatedly at monthly frequency, it is intuitive to construct a proxy for lottery-like features using daily returns from each month. However, the M&A setting is very different, because the sample consists of unique takeover events. Therefore, to capture the lottery-like features from the acquires and the targets before the announcements, I first need to determine a time horizon before the deal announcement to analyze their return distributions. Considering that successful M&As are the results of long-term negotiations and that investors usually evaluate M&As in a long horizon, in the main results, I analyze the returns patterns from acquirers and targets from the past 12 months before the deal announcement. I consider alternative variable constructions in robustness checks.

In my main results, the lottery-like feature of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement ($Max(3)$).[12] This is similar to the variable I construct for CEFs because I still use the top 25% of the returns to capture the right-tail of the return distribution. In robustness checks, I also consider using top-12 weekly returns ($Max(12)$) and top-60 daily returns ($Max(60)$) within the past year to capture lottery-like features for acquires and targets. $Max(60)$ is constructed in the same way as in the CEF setting, and will be adopted for the conglomerate setting as well. I also consider expanding the time horizon to examine lottery-like features to 24 months before the deal

[12] Other studies utilize monthly returns to capture the skewness of a return distribution, for instance, Mitton and Vorkink (2007), Mitton and Vorkink (2010), and Barberis, Mukherjee, and Wang (2016).

announcements. All these alternative specifications produce consistent results and are reported in Table 6.

For each M&A, I use $Combined\_Max(3)$, the weighted average $Max(3)$ from the acquirer and the target prior to the announcement, as a proxy for the overall lottery-like feature of the deal:

$$Combined\_Max(3) = w_A \times Max(3)_A + w_T \times Max(3)_T. \tag{11}$$

$Combined\_Max(3)$ only captures the lottery-like feature from the deal; it does not directly reflect the diversification in lottery-like features between the acquirer and the target. To explicitly show this, I construct a $CoMax$ proxy similar to the CEF setting to captures the likelihood that both the acquirer and the target pay out extreme returns at the same time.[13] Specifically, I define $CoMax(3)$ as the percentage of the top-3 monthly returns that are recorded in the same month. For example, if the top-3 monthly returns for Stock A come from month −10, −5 and −2, while the top-3 monthly returns for Stock B come from month −9, −5 and −3 (the month that the deal is announced is month 0), then $CoMax(3)$ equals 33% for this deal. By construction, $CoMax(3) \in [0,1]$. Weekly and daily versions of $CoMax$ are constructed in the same way in the robustness checks.

[13] Unlike the CEF setting, the lottery-like feature of the new joint firm is unobservable around the deal announcement, therefore, $CoMax$ is the best proxy for the diversification in lottery-like features in an M&A deal.

I consider the following control variables for both acquirers and targets: market capitalization, market-to-book ratio, return on assets, leverage, and operating cash flows. I consider the following control variables from deals: disagreement, relative size, tender offer, hostile offer, competing offer, cash only, stock only, and same industry. In addition, I control for the combined skewness and combined idiosyncratic volatility from the acquirer and the target. Detailed descriptions of these variables can be found in the Appendix.

My final sample contains 1,145 M&As from 1989 to 2014. Summary statistics are reported in Panel B of Table 1. The average $Combined\_Max(3)$ is 1.6% with a standard deviation of 7.0%.

3.3 Conglomerates

My last empirical setting is on conglomerates. A conglomerate is a firm operating in multiple industry segments. My data on firm segments is from Compustat. Each business segment is assigned a four-digit SIC code. I define a conglomerate as a firm operating across at least two different segments; I define a single-segment firm as a firm operating in only one segment. Following the 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 & Non-classifiable). 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 from any of the segments is missing or non-positive; (3) the sum of sales from all segments is not within one percent of the total sales of the firm; and (4) total sales of the firm is less than 20 million USD.

After screening out defective observations, I match the rest of the data to CRSP. More specifically, I match book value from fiscal year $t-1$ to market value at June of calendar year t, and compute market-to-book ratios for both conglomerates and single-segment firms. The market-to-book ratio for a segment (denoted as Seg_MEBE) is defined as the sales-weighted average market-to-book ratio across all single-segment firms within the segment. The imputed market-to-book ratio (defined as $Imputed\_MEBE$) is defined as the average Seg_MEBE across a conglomerate's segments, weighted by this conglomerate's net sales from each segment. The conglomerate discount is defined as the difference between a conglomerate's $Imputed\_MEBE$ and its own market-to-book ratio ($MEBE$), scaled by $Imputed\_MEBE$:

$$Discount_{i,t} = \frac{Imputed\_MEBE_{i,t} - MEBE_{i,t}}{Imputed\_MEBE_{i,t}} \quad . \tag{12}$$

I winsorize this variable at the 1st and 99th percentiles. Similar to the CEF setting, to avoid unnecessary confusion, I always describe the results in terms of discounts, 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 (i.e., the "portfolio") and the overall market value of the segments related to this conglomerate (i.e., the "underlying assets").

In contrast to the previous two samples, conglomerate discounts can be observed in each fiscal year, while CEF discounts are observed monthly and M&A announcements are unique events. Therefore, to capture the lottery-like feature for a conglomerate's business segments, it is reasonable to construct a proxy at an annual frequency using returns within the fiscal year. In light of this, I use the average top-3 monthly returns within the fiscal year (denoted as $Max(3)$) to capture lottery-like features in this setting. This is the same proxy adopted in the M&A setting, and it is consistent with the CEF setting since the top 25% of the returns are used to capture the right-tail of the return distribution. In robustness checks, I also consider using the top-12 weekly returns ($Max(12)$) and the top-60 daily returns ($Max(60)$) within the year. $Max(60)$ is constructed in the same way as in the CEF and M&A settings. In addition, I also consider expanding the time horizon to observe return distributions within the past two fiscal years. All these alternative proxies produce similar results and are reported in Table 6.

I construct lottery-like features for business segments from single-segment firms in the relevant business segments. When analyzing the lottery-like features of single-segment firms that are associated with a conglomerate, I only consider five single-segment firms from each segment that the conglomerate operates within, based on the closeness of SIC code first and then net sales.[14] The reasons are as follows. First, the full lists of single-segment firms as defined by SIC codes are

[14] If there are fewer than 5 single-segment firms found at the 4-digit SIC level, I proceed to the 3-digit SIC level, and to the 2-digit SIC level if necessary, until at least 5 single-segment matching firms are found. If less than 5 matching firms are found at the 2-digit SIC level, the observation is excluded.

not readily available. Therefore, it is hard for investors to collect all the single-segment firms that may be potentially associated with a conglomerate. Second, some business segments do have a lot of single-segment firms.[15] It is difficult for investors to keep all these firms in mind. Finally, to reduce potential noise associated with my empirical tests, I choose the single-segment firms that are comparable to the conglomerate within each respective business segment.

The lottery-like feature for each segment (denoted as $Seg\_Max(3)$) is defined as the sales-weighted average $Max(3)$ across the five single-segment firms selected. $Imputed\_Max(3)$ is defined as the average $Seg\_Max(3)$ across a conglomerate's segments, weighted by this conglomerate's net sales from each segment.

Similar to the construction in the first two settings, in order to directly show the effect of the diversification in lottery-like features among all business segments, I construct $CoMax$, to capture the tendency that lottery-like payoffs are produced together. Specifically, I construct $CoMax(3)$ for all possible stock pairs $\{i, j\}$ from any two different segments $\{m, n\}$.[16] For example, consider a conglomerate that operates in three different segments, A, B, and C. This conglomerate has three segment pairs: $\{A, B\}$, $\{A, C\}$, and $\{B, C\}$. Given segment pair $\{A, B\}$, I choose one of the five single-segment firms from Segment A, and one of the five single-

[15] For example, "Services-Prepackaged Software" (SICCD = 7372) has around 90 single-segment firms on average, and "Semiconductors & Related Devices" (SICCD = 3674) has more than 50 single-segment firms on average

[16] The most obvious choice, which is using value-weighted average returns from each segment, does not serve the purpose here. Aggregating returns at the segment level diversifies away lottery-like features.

segment firms from Segment B. This exercise leaves me 25 (5×5) stock pairs $\{A_i, B_j\}$. After computing the percentage of the top-3 monthly returns that are recorded in the same month for each stock pair (denoted as $CoMax_{A_i,B_j}$), I take the sales-weighted average across the 25 pairs constructed between Segment A and Segment B (denoted as $Seg\_CoMax_{A,B}$). I repeat the exercise for the other two segment pairs. Finally, I define $CoMax(3)$ as the average of $Seg\_CoMax_{m,n}$ $(m, n \in \{A, B, C\})$, weighted by this conglomerate's net sales from each segment pairs. $Pair\_Max(3)_{m_i,n_j}$ and $Pair\_Max(3)_{m_i,n_j} \times CoMax(3)_{m_i,n_j}$ are constructed using the same procedure and then aggregated to the conglomerate-level (denoted as $Imputed\_Max(3)$ and $Pair\_Max(3) \times CoMax(3)$). Note that, after taking the weighted average of $Pair\_Max(3)_{m_i,n_j}$ across all stock pairs and then segment pairs, the result becomes exactly $Imputed\_Max(3)$, because each stock is counted twice. This method is in the same spirit with Green and Hwang (2012), who pool returns from all stocks in each of the FF-30 industries to compute that industry's skewness. My method is similar in spirit, as I pool a collection of individual stock returns to capture lottery-like features and $CoMax$ for segments.

Control variables for this setting include: $Cong\_Max(3)$ (the average top-3 monthly returns within a year for a conglomerate), disagreement, total assets, leverage, profitability, and investment ratio. In addition, I include excess skewness and excess idiosyncratic volatility. I also control for imputed skewness and imputed 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).

4 Main Results

In this section, I document three sets of empirical evidence to support the model prediction in Section 2: CEFs (Section 4.1), M&A (Section 4.2), and conglomerates (Section 4.3). In all three settings, the diversification in lottery-like features help explain the portfolio pricing discount.

4.1 Closed-end Funds

My main tests focus on CEFs. I estimate pooled OLS regressions with fixed effects and with standard errors clustered along both fund and time dimensions. The dependent variable is the monthly CEF discount (in percentage). It captures the difference between the market value of the fund and the market value of its holdings.

Control variables include: $CEF\_Max(5)$, disagreement, inverse CEF price, dividend yield, liquidity ratio, expense ratio, weighted average skewness and idiosyncratic volatility from holdings. Detailed descriptions of the control variables can be found in the Appendix. Hwang (2011) argues that inverse price and dividend yield have differential predictions on the CEF discount 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 the inverse price if the fund trades at a discount and zero otherwise. $Dividend\ Yield[pos]$ and $Dividend\ Yield[neg]$ are defined in a similar fashion. All independent variables are standardized to have a mean of zero and a standard deviation of one. The results are reported in Table 2.

[Table 2 Here]

Table 2 confirms the model prediction in Section 2. First, in all columns, the coefficients on $Holding\_Max(5)$ are positive and significant. In other words, if a CEF's holdings exhibit strong lottery-like features, the CEF will be traded at a higher discount. On the other hand, the coefficients on $Pair\_Max(5) \times CoMax(5)$ are all negative and significant. This indicates that if a CEF's holdings exhibit strong lottery-like features and they tend to produce extreme payoffs together, the CEF discount can be partially mitigated. In Column (6), after controlling for $CEF\_Max(5)$, other variables associated with CEF discounts, and fund and time fixed effects, a one-standard-deviation increase in $Holding\_Max(5)$ comes with a 1.94% increase in the CEF discount (*t*-statistic = 4.33). Meanwhile, a one-standard-deviation increase in $Pair\_Max(5) \times CoMax(5)$ can help offset the diversification effect by 0.49% (*t*-statistic = −3.97). Considering that the average CEF discount in my sample is 4.70%, these results are both statistically significant and economically large.

The difference in prices between the portfolio and its components is potentially an arbitrage opportunity. Therefore, the variation of limits-to-arbitrage may have an impact on my results. To further investigate on this issue, I consider two proxies for limits-to-arbitrage. First, I use TED spread as a time-series proxy for arbitrageurs' funding costs. A high TED spread indicates a worse arbitrage condition. I find that, during high TED spread periods, a one-standard-deviation increase in $Holding\_Max(5)$ comes with a 2.25% increase in the CEF discount (*t*-statistic = 4.15), while a one-standard-deviation increase in $Pair\_Max(5) \times CoMax(5)$ can help offset the diversification effect by 0.52% (*t*-statistic = −3.20). On the other hand, during low TED spread periods, a one-standard-deviation increase in $Holding\_Max(5)$ only comes with a 0.01% increase in the CEF discount (*t*-statistic = 0.01), while a one-standard-deviation increase in $Pair\_Max(5) \times CoMax(5)$ can help offset the diversification effect by 0.07% (*t*-statistic = −0.17).

Second, I use average institutional ownership from a CEF's holding stocks as a cross-sectional proxy for limits-to-arbitrage. I find that, among CEFs with low average institutional ownership, a one-standard-deviation increase in $Holding\_Max(5)$ comes with a 2.36% increase in the CEF discount (*t*-statistic = 3.45), while a one-standard-deviation increase in $Pair\_Max(5) \times CoMax(5)$ can help offset the diversification effect by 0.49% (*t*-statistic = −5.07). Among CEFs with high average institutional ownership, a one-standard-deviation increase in $Holding\_Max(5)$ only comes with a 1.76% increase in the CEF discount (*t*-statistic = 2.63), while a one-standard-deviation increase in $Pair\_Max(5) \times CoMax(5)$ can help offset the diversification effect by 0.37% (t-statistic = −0.83).

Both of these two tests suggest that the variation of limits-to-arbitrage have an impact on my proposed mechanism. The relation between diversification in lottery-like features and CEF discount is stronger when limits-to-arbitrage is high.[17]

4.2 M&A

I estimate pooled OLS regressions with time-fixed effects and with standard errors clustered by time across 1,145 M&A events that meet data requirements. The dependent variable is the combined announcement return ($Combined\_CAR\ [-1,+1]$) (in percentage), where $t = 0$ is the announcement day, or the ensuing trading day if the deal is announced when the market is closed. I control characteristics from acquirers, targets and deals. Detailed description of all of the control variables can be found in the Appendix. All variables are standardized to have a mean of zero and a standard deviation of one. Results are reported in Table 3.

[Table 3 Here]

Table 3 provides results consistent with the model prediction. In all columns, the coefficients on $Combined\_Max(3)$ is negative and significant. That is, if a M&A deal has a stronger lottery-like feature, the deal will have a lower combined announcement return. In other words, the market

[17] For brevity, these results are not tabulated and are available upon requests.

value of the new joint firm will be discounted. On the other hand, the coefficients on $Combined\_Max(3) \times CoMax(3)$ are all positive and significant. That is, if a M&A deal has a strong lottery-like feature and the acquirer and the target tend to provide extreme returns at the same time, the discount effect can be partially mitigated. In Column (4), after controlling for various factors associated with M&A announcement returns and time fixed effects, a one-standard-deviation increase in $Combined\_Max(3)$ comes with a 1.73% decrease in the combined announcement return (*t*-statistic = 3.03). Meanwhile, a one-standard-deviation increase in $Combined\_Max(3) \times CoMax(3)$ can help offset the diversification effect by 0.74% (*t*-statistic = 4.00). Considering that the mean $Combined\_CAR\ [-1,+1]$ in my sample is about 1.60%, these results are both statistically significant and economically large.

4.3 Conglomerate Firms

I estimate pooled OLS regressions with time fixed effects and standard errors clustered by firm and time. The dependent variable is the conglomerate discount (not in percentage). This variable captures the difference between the market value of a conglomerate (i.e., the "portfolio") and the average market value of the segments associated with the conglomerate's business (i.e., the "underlying assets").

Control variables include: $Cong\_Max(3)$, disagreement, log total assets, the square of log total assets, leverage, profitability, investment ratio, imputed skewness, and imputed idiosyncratic volatility. Detailed descriptions of the control variables can be found in the Appendix. All independent 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]

Table 4 confirms the model prediction in Section 2. First, in all columns, the coefficients on $Imputed\_Max(3)$ are positive and significant. In other words, if a conglomerate's business segments exhibit stronger lottery-like features, the conglomerate will have a lower market-to-book ratio. On the other hand, the coefficients on $Pair\_Max(3) \times CoMax(3)$ are all negative and significant. This indicates that if a conglomerate's business segments exhibit strong lottery-like features and they tend to produce extreme payoffs together, the conglomerate discount can be partially mitigated. In Column (5), after controlling for $Cong\_Max(3)$, other variables associated with conglomerate discounts, and time fixed effects, a one-standard-deviation increase in $Imputed\_Max(3)$ comes with a 17.3% increase in the conglomerate discount (t-statistic = 4.55). Meanwhile, a one-standard-deviation increase in $Pair\_Max(3) \times CoMax(3)$ can help offset the diversification effect by 8.0% (t-statistic = 3.48). Considering that the average conglomerate discount in my sample is 13.0%, these results are both statistically significant and economically large.

In a related study, Mitton and Vorkink (2010) show that the size of the conglomerate discount is related to the difference between the skewness of a conglomerate and the average skewness of matched single-segment firms. I find a similar result using the difference between $Cong\_Max(3)$

and $Imputed\_Max(3)$. However, these two proxies are aggregated measures which do not directly capture the diversification effect in lottery-like features among different business segments, and they might be potentially driven by returns from conglomerates. Taking a different approach from Mitton and Vorkink (2010), My empirical design introduces $CoMax(3)$ to directly capture the diversification in lottery-like features among different business segments. More importantly, $Pair\_Max(3) \times CoMax(3)$ does not rely on the prices and returns from a conglomerate. Through this unique empirical design and an explicit theoretical foundation to illustrate the economic intuition, my results build upon those of Mitton and Vorkink (2010) showing that if business segments have strong lottery-like features and a high tendency to producing extreme returns at the same time, the conglomerate discount will be partially mitigated.

5 Robustness

5.1 Placebo Tests

A potential concern for the results documented in Sections 4 is that $CoMax$ may simply capture return correlation. This is a fair challenge because $CoMax$ and return correlation are mechanically correlated. To address this concern, I conduct three placebo tests (one for each setting). In each placebo test, I replace $CoMax$ with a return correlation constructed after excluding the extreme returns that are recorded at the same time.

Take the CEF setting as an example. For each stock pair from a CEF's top-10 holdings, I retrieve the daily return series for both stocks during the month, and exclude any of the top-5 returns that are recorded in the same day. For example, if the top-5 daily returns for Stock A come from the 1st, 4th, 9th, 11th, and 15th day of the month, while the top-5 daily returns for stock B come from the 2nd, 4th, 9th, 14th, and 20th day of the month, then daily returns for Stock A and B on the 4th & 9th day of the month are excluded. Then, I calculate the return correlation between the two stocks using the rest of the daily returns and denote this correlation as $Non\_Max\_Corr_{i,j}$. I compute $Non\_Max\_Corr_{i,j}$ and $Pair\_Max5_{i,j} \times Non\_Max\_Corr_{i,j}$ for all possible top-10 stock pairs and take the weighted average (denoted as Non_Max_Corr and $Pair\_Max(5) \times Non\_Max\_Corr$). I replace $CoMax(5)$ with Non_Max_Corr, replace $Pair\_Max(5) \times CoMax(5)$ with $Pair\_Max(5) \times Non\_Max\_Corr$, and reconduct the regressions in Table 2. I report these results in Panel A of Table 5. The interaction term $Pair\_Max(5) \times Non\_Max\_Corr$ becomes insignificant.

[Table 5 Here]

For the M&A sample, I first retrieve the monthly return series from the past year for both the acquirer and the target, and then exclude any of the top-3 monthly returns that are recorded in the same month. For example, if the top-3 monthly returns for Stock A come from month −10, month −5, and month −2 (the month that the deal is announced is month 0), while the top-3 monthly returns for Stock B come from month −9, month −5, and month −3, then the monthly returns for

Stock A and B on month -5 are excluded. I calculate the return correlation between the acquirer and the target using the rest of the monthly returns, and denote this correlation as Non_Max_Corr. I replace $CoMax(3)$ by Non_Max_Corr, replace $Combined\_Max(3) \times CoMax(3)$ by $Combined\_Max(3) \times Non\_Max\_Corr$, and reconduct the regressions in Table 4. I report these results in Panel B of Table 5. The interaction term $Combined\_Max(3) \times Non\_Max\_Corr$ becomes insignificant.

Finally, I exploit the setting of conglomerates. For each of the two stocks $\{i, j\}$ from segment pair $\{m, n\}$, I retrieve the monthly return series within the fiscal year for both stocks and exclude any of the top-3 monthly returns that are recorded in the same month. I calculate the return correlation between the two stocks using the rest of the monthly returns, and denote this correlation as $Non\_Max\_Corr_{m_i,n_j}$. I compute $Non\_Max\_Corr_{m_i,n_j}$ and $Pair\_Max(3)_{m_i,n_j} \times Non\_Max\_Corr_{m_i,n_j}$ for every two stocks $\{i, j\}$ from segment pair $\{m, n\}$, and take the weighted average to get $Non\_Max\_Corr_{m,n}$ and $Pair\_Max(3)_{m,n} \times Non\_Max\_Corr_{m,n}$. I do this for every segment pairs and then take the weighted average to get Non_Max_Corr and $Pair\_Max(3) \times Non\_Max\_Corr$ at the conglomerate level. I replace $CoMax(3)$ with Non_Max_Corr, replace $Pair\_Max(3) \times CoMax(3)$ with $Pair\_Max(3) \times Non\_Max\_Corr$, and reconduct the regressions in Table 5. I report these results in Panel C of Table 5. The interaction term $Pair\_Max(3) \times Non\_Max\_Corr$ becomes insignificant.

These three tests all show that return correlations during non-$CoMax$ periods cannot explain CEF discounts, M&A announcement returns, or conglomerate discounts. All results reported in this section further support the model prediction that the diversification in lottery-like features, not return correlation, can help explain the portfolio pricing discount.

5.2 Alternative Proxies for Lottery-like Features

In this section, I examine the robustness of the results in Section 4 by considering alternative proxies for lottery-like features. In all three settings, using alternative proxies produces consistent results.

First, in the CEF setting, the lottery-like feature is defined as the average top-5 daily returns within a month. This proxy uses the top 25% of the data to capture the right tail of the return distribution. To examine if my results are sensitive to this top 25% cut off, I consider using the average top-2 and top-3 daily returns within a month to proxy for lottery-like features, and denote them as $Max(2)$ and $Max(3)$.

Since the time window to capture lottery-like features in Sections 4.2-4.3 is one year, I also consider another proxy for CEFs based on the top-60 daily returns in the past year and denote it as $Max(60)$. $Max(60)$ is similar to $Max(5)$ as I still use about the top 25% of the data to capture the right tail of the return distribution.

$Holding\_Max(i)$, $CoMax(i)$, $Pair\_Max(i)$, and $Pair\_Max(i) \times CoMax(i)$ ($i = 2, 3, 60$) are constructed using the same procedure as outlined in Section 3.1. I use these alternative proxies to reconduct my analysis in Table 2 and report the results in Panel A of Table 6. I find consistent results similar to what I have documented in Section 4.1.

In the M&A setting, the lottery-like feature is captured by the average top-3 monthly returns within the 12 months prior to the deal announcement. I consider three different ways to construct proxies for lottery-like features. First, I use an alternative observation window of 24 months prior to the announcement, and I use the average top-5 monthly returns (denoted as $Max(5)$) to capture lottery-like features from the acquirer and the target. Second, I define $Max(12)$ as the average top-12 weekly returns within the 12 months prior to the announcement. Finally, I define $Max(60)$ as the average top-60 day returns within the 12 months prior to the announcement. In all three proxies, around the top 25% of the data is used to capture the right-tail of the return distribution, consistent with what I have adopted in the main results. $Combined\_Max(i)$, $CoMax(i)$, and $Combined\_Max(i) \times CoMax(i)$ ($i = 5{,}12{,}60$) are constructed using the same procedure as outlined in Section 3.2. I use these alternative proxies to reconduct my analysis in Table 3 and report the results in Panel B of Table 6. I find consistent results similar to what I have documented in Section 4.2.

In the conglomerate setting, the lottery-like feature is captured by the average top-3 monthly returns within the fiscal year. I consider three different ways to construct proxies for lottery-like features. First, I use the past two fiscal years as an alternative observation window and the average top-5 monthly returns ($Max(5)$) to capture the lottery-like feature. Second, I define $Max(12)$ as the average top-12 weekly returns within the fiscal year. Finally, I define $Max(60)$ as the average top-60 daily returns within the fiscal year. In all three proxies, around the top 25% of the data is used to capture the right-tail of the return distribution, consistent with what I have adopted in the main results. $Imputed\_Max(i)$, $CoMax(i)$, $Pair\_Max(i)$ and $Pair\_Max(i) \times CoMax(i)$ ($i = 5$,12,60) are constructed using the same procedure as outlined in Section 3.3. I use these alternative proxies to reconduct my analysis in Table 4 and report the results in Panel C of Table 6. I find consistent results similar to what I have documented in Section 4.3.

All three panels from Table 6 show that my main results are robust across alternative definitions for lottery-like features constructed from monthly returns, weekly returns, daily returns, and different time horizons. In all three settings, the diversification in lottery-like features contributes to the portfolio pricing discount, consistent with the predictions of cumulative prospect theory.

6 Conclusion

In this paper, I study a new asset pricing implication of cumulative prospect theory. Previous research on this topic mainly focused on the shape of the value function or the negative expected returns from lottery-like stocks in the cross-section. My paper takes a novel and less-studied perspective: portfolio discounts. Specifically, I extend cumulative prospect theory based on Barberis and Huang (2008) in a portfolio setting and show that a portfolio consisting of lottery-like stocks should trade at a discount. I solve and compare asset prices in two economies. In the first economy, investors can trade these lottery-like stocks freely. In the second economy, investors can only trade a portfolio consisting of these lottery-like stocks. I find that the portfolio price in the second economy is lower than the prices of these lottery-like stocks in the first economy. More importantly, this discount depends on how likely these lottery-like stocks are to produce extreme payoffs at the same time. Specifically, when the stocks are more likely to produce extreme payoffs at the same time, the portfolio pricing discount is lower.

I utilize CEFs, M&As, and conglomerates to test this prediction and find consistent results. In all three settings, the diversification in lottery-like features can help explain the CEF discounts, the combined announcement returns of M&As, and the conglomerate discounts. On the other hand, when underlying assets have strong lottery-like features and are more likely to produce extreme payoffs at the same time, these portfolio pricing discounts can be partially mitigated.

My paper extends cumulative prospect theory to new territories to evaluate three seemingly unrelated phenomena. My empirical analyses support cumulative prospect theory from a novel perspective by comparing the value of the portfolio and the total value of its underlying assets.

Finally, I provide a new and unifying explanation on the CEF puzzle, the M&A announcement return, and the conglomerate discount.

My paper also has managerial implications. A CEF manager may be better off avoiding lottery-like stocks at fund inception. When evaluating potential M&A deals, a CEO should take advantage of the lottery-like feature of the firm by finding a lottery-like counterpart with a high $CoMax$. Finally, it may be beneficial in terms of valuation for a conglomerate to unbundle its giant empire into smaller firms with more focused businesses.

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Appendix 1. Variable Definitions

A1.1. Closed-end Funds

CEF_Max(5): The top-5 daily returns within a month for a closed-end fund.

Disagreement: The portfolio-weighted average price-scaled earnings forecast dispersion of the top-10 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, I divide the number of shares traded by two.

Expense Ratio: The expense ratio of the CEF.

Holding Skewness: The portfolio-weighted average skewness from top-10 holdings. Return skewness is calculated using daily returns over a one-year window.

Holding Idiosyncratic Volatility: The portfolio-weighted average idiosyncratic volatility from top-10 holdings. Idiosyncratic volatility is estimated based on residuals from Fama-French 3-factor model over a one-year window using daily returns.

A1.2. Mergers and Acquisitions

Disagreement: The average price-scaled earnings forecast dispersion 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) earnings before interest and tax over total assets.

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

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

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

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

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

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

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

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

Same Industry: A dummy variable that equals one if the acquirer and target companies have the same two-digit SIC code, and zero otherwise.

Combined Skewness: The weighted average return skewness from the acquirer and the target. Return skewness is calculated using daily returns over a one-year window before the announcement.

Combined Idiosyncratic Volatility: The weighted average idiosyncratic volatility from the acquirer and the target. Idiosyncratic volatility is estimated based on residuals from the Fama-French 3-factor model using daily returns over a one-year window before the announcement.

A1.3. Conglomerates

Cong_Max(3): The average top-3 monthly returns from the past year for a conglomerate.

Disagreement: For each of the conglomerate's underlying segments, I calculate the average price-scaled earnings forecast dispersion across single-segment firms in that segment. Disagreement is the sales-weighted average of the conglomerate's underlying segment dispersions.

Total Assets: The conglomerate's total assets.

Leverage: The conglomerate's long-term debt over total assets.

Profitability: The conglomerate's earnings before interest and tax over net revenue.

Investment Ratio: The conglomerate's capital expenditure over net revenue.

Imputed Skewness: The sales-weighted average skewness from a conglomerate's business segments, where the skewness of each segment is computed as the weighted average skewness across single-segment firms in that segment. Return skewness is calculated using daily returns over a one-year window

Imputed Idiosyncratic Volatility: The sales-weighted average idiosyncratic volatility from a conglomerate's business segments, where the idiosyncratic volatility of each segment is computed as the weighted average idiosyncratic volatility across single-segment firms in that segment. Idiosyncratic volatility is estimated based on residuals from the Fama-French 3-factor model over a one-year window using daily returns.

Appendix 2. Equilibrium Conditions for Economy II

In the second economy in Section 2.2, two types of equilibria may exist, depending on parameters. A homogeneous holdings equilibrium is an equilibrium in which all investors hold the same position. In this equilibrium, each investor will hold an infinitesimal amount ε^* of the portfolio. Following Proposition 2 in Barberis and Huang (2008), the expected excess return on this portfolio should be zero, or more precisely, infinitesimally greater than zero.

$$E(r_s) = u\left(\frac{J}{p_s} - r_f\right) + (2v - 2u)\left(\frac{J}{2p_s} - r_f\right) - (1 - 2v + u)r_f = 0 \ . \tag{13}$$

i.e.,

$$p_s = \frac{vJ}{r_f} \ . \tag{14}$$

Note that in a homogeneous holdings equilibrium, the price of the portfolio, p_s, does not depend on u.

The other type of equilibrium is a heterogenous holdings equilibrium with two groups of investors (these investors are ex-ante homogeneous), where the first group holds a combination of the risk-free asset, the market portfolio, and the new portfolio; and the second group holds the risk-free asset and the market portfolio but takes no position in the new portfolio. Markets are cleared by assigning each investor to one of the optima. According to Barberis and Huang (2008), a heterogeneous holdings equilibrium should satisfy the following conditions:

$$V(r_m) = V(r_m + \phi^* r_s) = 0 \ , \tag{15}$$

$$V(r_m + \phi r_s) < 0 \quad for \quad 0 < \phi \neq \phi^*, \tag{16}$$

$$V(r_s) < 0 \ , \tag{17}$$

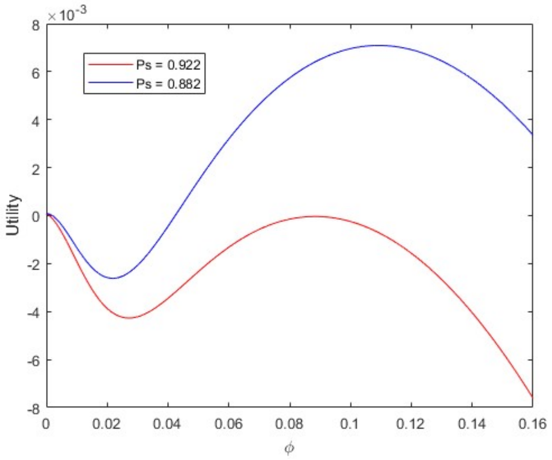
where

$$V(r_m + \phi r_s) = -\int_{-\infty}^{0} w\left(P_\phi(r)\right) dv(r) + \int_{0}^{\infty} w\left(1 - P_\phi(r)\right) dv(r) \ , \tag{18}$$

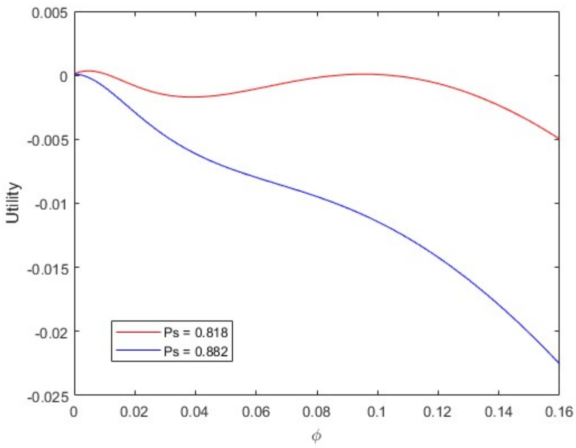
and

$$\begin{aligned}
P_\phi(r) &= \Pr(r_m + \phi r_s \le r) \\
&= \Pr\left(r_s = \frac{J}{p_s} - r_f\right) \Pr\left(r_m \le r - \phi\left(\frac{J}{p_s} - r_f\right)\right) \\
&\qquad + \Pr\left(r_s = \frac{J}{2p_s} - r_f\right) \Pr\left(r_m \le r - \phi\left(\frac{J}{2p_s} - r_f\right)\right) \\
&\qquad + Pr(r_s = -r_f) \Pr(r_m \le r + \phi r_f) \\
&= uN\left(\frac{r - \phi\left(\frac{J}{p_s} - r_f\right) - \mu_m}{\sigma_m}\right) + 2(v-u)N\left(\frac{r - \phi\left(\frac{J}{2p_s} - r_f\right) - \mu_m}{\sigma_m}\right) \\
&\qquad + (1 - 2v + u)N\left(\frac{r + \phi r_f - \mu_m}{\sigma_m}\right),
\end{aligned} \tag{19}$$

Here, ϕ (ϕ^*) is the (optimal) fraction of wealth allocated to the new portfolio relative to the fraction allocated to the market portfolio for investors from the first group, and $N(\cdot)$ is the cumulative normal distribution function. In a heterogeneous holdings equilibrium, the price of the portfolio, p_s, does not have an analytical solution. It depends not only on the lottery-like feature from its holdings (v), but also on the probability that both lottery-like stocks pay out "jackpots" at the same time ($CoMax$).



(a) $u = 0.08$



(b) $u = 0.01$

Figure 1 Heterogeneous Holdings Equilibrium and Homogeneous Holdings Equilibrium

This figure demonstrates the utility that investors with cumulative prospect theory preferences derives from adding a position in a portfolio which equally invests in two lottery-like stocks to their current holdings of a normally distributed market portfolio. The variable ϕ is the fraction of wealth allocated to the portfolio relative to the fraction of wealth allocated to the market portfolio. The variable u is the probability that both lottery-like stocks pay out "jackpots" at the same time. In Figure 1a, $u = 0.08$, while in Figure 1b, $u = 0.01$. The price of the portfolio is denoted as p_s. Both figures use the following parameters: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$. In both figures, the red line is based on the price of the portfolio from a heterogenous holdings equilibrium, and the blue line is based on the price of the portfolio from a homogenous holdings equilibrium.

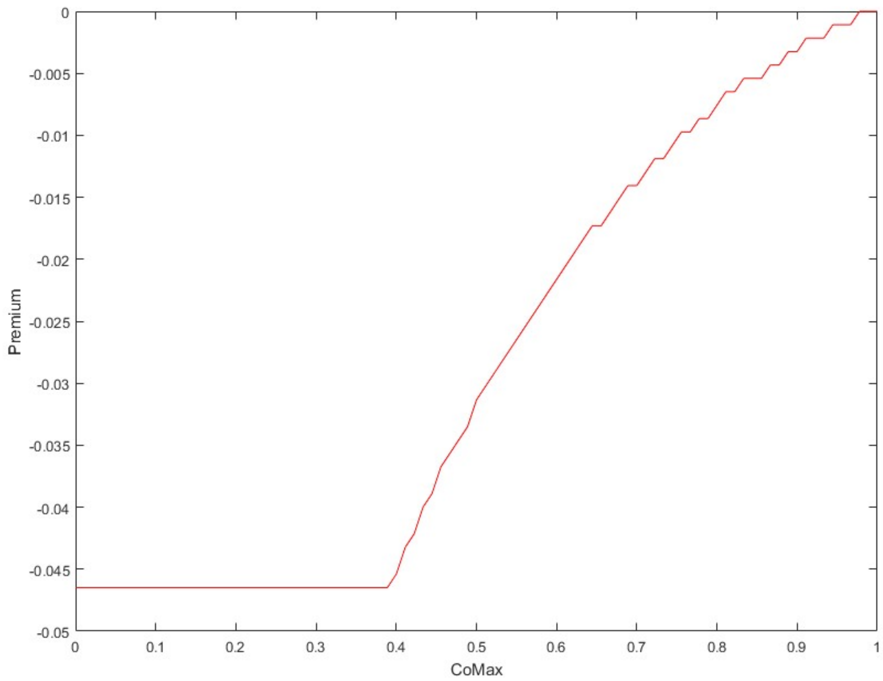
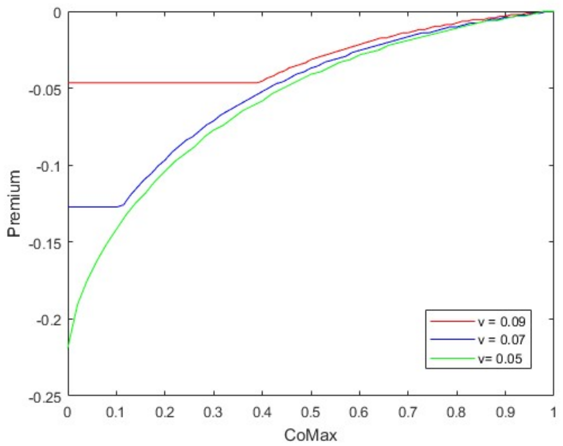
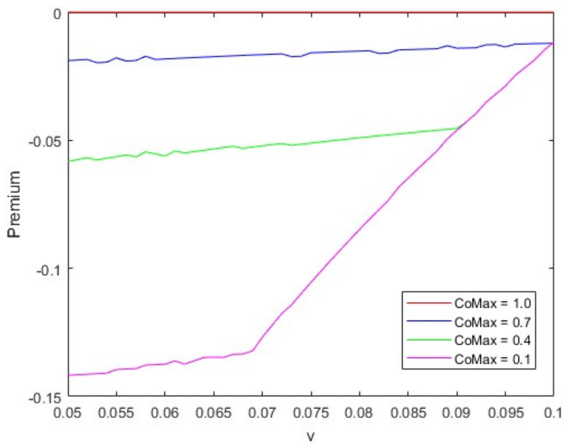


Figure 2 Portfolio Discount and $CoMax$

This figure plots the price discount of a portfolio which equally invests in two lottery-like stocks as a function of $CoMax$. $CoMax = u/v$, where v is the probability that each lottery-like stock pays out "jackpots", and u is the probability that both lottery-like stocks pay out "jackpots" at the same time. I use the following parameters to search the equilibrium prices for the portfolio: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$. For each value of $CoMax$, I search for a heterogeneous holdings equilibrium first, and if it does not exist, a homogenous holdings equilibrium.



(a)



(b)

Figure 3 v, $CoMax$ and Portfolio Discount

This figure plots the price discount of a portfolio which equally invests in two lottery-like stocks as a function of (a) $CoMax$, the tendency that both lottery-like stocks pay off "jackpots" at the same time; and (b) v, the degree of lottery-like feature for each lottery-like stock. I use the following parameters to search the equilibrium prices for the portfolio: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J) = (0.15, 1.02, 10)$. For each $CoMax$ and v, I search for a heterogeneous holdings equilibrium first, and if it does not exist, a homogenous holdings equilibrium.

Table 1 Descriptive Statistics

This table presents descriptive statistics for CEFs (Panel A), M&A deals (Panel B), and conglomerates (Panel C). In Panel A, CEF Discount is defined as the difference between a CEF's NAV and the CEF price, divided by NAV. I use the average top-5 daily returns within a month (*Max(5)*) to proxy for lottery-like feature for the CEF and its holdings. I denote *CEF_Max(5)* as the *Max(5)* for a CEF and *Holding_Max(5)* as the average *Max(5)* from a CEF's top-10 holdings, weighted by holding percentage. For each possible stock pairs among the top ten holdings, $CoMax(5)_{i,j}$ is the percentage of top-5 daily returns that are recorded in the same day, and $Pair\_Max(5)_{i,j}$ is the average *Max(5)* of the stock pair, weighted by holding percentage. $Pair\_Max(5)_{i,j}$, $CoMax(5)_{i,j}$, and $Pair\_Max(5)_{i,j} \times CoMax(5)_{i,j}$ are then taken weighted average across all stock pairs (denoted as *Holding_Max(5)*, *CoMax(5)*, and *Pair_Max(5)×CoMax(5)*). Note that after $Pair\_Max(5)_{i,j}$ is taken weighted average across all stock pairs, it equals *Holding_Max(5)*. In Panel B, *Combined_CAR [−1,+1]*, i.e., the combined announcement return, is 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, where $t = 0$ is the announcement day, or the ensuing trading day if the deal is announced when the market is closed. The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max(3)_A$ and $Max(3)_T$). *Combined_Max(3)* is the average of $Max(3)_A$ and $Max(3)_T$, weighted by their respective market capitalizations in the month prior to the announcement. *CoMax(3)* is the percentage of the top-3 monthly returns that are recorded in the same month. In Panel C, the conglomerate discount is defined as the difference between a conglomerate's *Imputed_MEBE* and its own market-to-book ratio, scaled by *Imputed_MEBE*, where *Imputed_MEBE* is defined as the average *Seg_MEBE* across a conglomerate's segments weighted by this conglomerate's net sales from each segment, and *Seg_MEBE* is defined as the sales-weighted average market-to-book values across single-segment firms within each segment. The lottery-like feature for a firm is proxied by the average top-3 monthly returns within the fiscal year (*Max(3)*). *Cong_Max(3)* is the *Max(3)* from a conglomerate. *Imputed_Max(3)* is the average *Seg_Max(3)* across a conglomerate's segments, weighted by this conglomerate's net sales from each segment, and *Seg_Max(3)* is the sales-weighted average *Max(3)* across five single-segment firms chosen similar to the conglomerate's operation in that segment based on SIC code and sales. $CoMax(3)_{m(i),n(j)}$ is the percentage of top-3 monthly returns that are recorded in the same month for every possible stock pairs *{i,j}* constructed from any two different underlying segments *{m,n}*, and $Pair\_Max(3)_{m(i),n(j)}$ is the average *Max(3)* from these two stocks. $Pair\_Max(3)_{m(i),n(j)}$, $CoMax(3)_{m(i),n(j)}$, and $Pair\_Max(3)_{m(i),n(j)} \times CoMax(3)_{m(i),n(j)}$ are then taken weighted average across all stock pairs and segment pairs (denoted as *Imputed_Max(3)*, *Pair_Max(3)*, and *Pair_Max(3)×CoMax(3)*). Note that after $Pair\_Max(3)_{m(i),n(j)}$ is taken weighted average across all stock pairs and then segment pairs, it equals *Imputed_Max(3)*. The definitions of all control variables are described in the appendix.

Panel A: Closed-end Funds						
Variables	**N**	**Mean**	**StdDev**	**p25**	**p50**	**p75**
CEF Discount	2330	0.047	0.143	0.025	0.090	0.124
Holding_Max(5)	2330	0.020	0.010	0.014	0.017	0.022
Pair_Max(5)×CoMax(5)	2330	0.063	0.129	0.026	0.039	0.062
CoMax(5)	2330	0.445	0.102	0.372	0.436	0.512
CEF_Max(5)	2330	0.014	0.010	0.008	0.011	0.015
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
Holding_Tskew	2330	0.164	0.428	-0.085	0.086	0.320
Holding_Ivol	2330	0.013	0.005	0.009	0.011	0.014

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_Max(3)	1145	0.154	0.099	0.091	0.129	0.186
Combined_Max(3)×CoMax(3)	1145	0.062	0.068	0.023	0.046	0.081
CoMax(3)	1145	0.380	0.256	0.333	0.333	0.667
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

(*Continued*)

(*Continued*)

Variables	N	Mean	StdDev	p25	p50	p75
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	0.244	0.816	-0.070	0.219	0.529
Combined_Ivol	1145	0.022	0.011	0.014	0.019	0.027

Panel C: Conglomerates

Variables	N	Mean	StdDev	p25	p50	p75
Conglomerate Discount	15907	0.130	0.981	-0.171	0.292	0.583
Imputed_Max(3)	15907	0.157	0.111	0.092	0.129	0.187
Pair_Max(3)×CoMax(3)	15907	0.027	0.014	0.017	0.024	0.032
CoMax(3)	15907	0.329	0.087	0.270	0.320	0.380
Cong_Max(3)	15907	0.143	0.053	0.109	0.133	0.166
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
Imputed_Tskew	15907	0.214	0.517	-0.001	0.247	0.472
Imputed_Ivol	15907	0.022	0.008	0.017	0.021	0.026

Table 2 Closed-end Fund Discounts

This table reports coefficient estimates from regressions of CEF discounts on measures of the lottery-like features. The dependent variable is the CEF discount, defined as the difference between a CEF's NAV and its own market price, divided by NAV (expressed in %). I use the average top-5 daily returns within a month (*Max(5)*) to proxy for lottery-like feature for the CEF and its holdings. I denote *CEF_Max(5)* as the *Max(5)* for a CEF and *Holding_Max(5)* as the average *Max(5)* from a CEF's top-10 holdings, weighted by holding percentage. For each possible stock pairs among the top ten holdings, $CoMax(5)_{i,j}$ is the percentage of top-5 daily returns that are recorded in the same day, and $Pair\_Max(5)_{i,j}$ is the average *Max(5)* of the stock pair, weighted by holding percentage. $Pair\_Max(5)_{i,j}$, $CoMax(5)_{i,j}$, and $Pair\_Max(5)_{i,j} \times CoMax(5)_{i,j}$ are then taken weighted average across all stock pairs (denoted as *Holding_Max(5)*, *CoMax(5)*, and *Pair_Max(5)×CoMax(5)*). Note that after $Pair\_Max(5)_{i,j}$ is taken weighted average across all stock pairs, it equals *Holding_Max(5)*. Detailed description of all control variables can be found in the appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. I estimate fixed effect regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. Columns (1)-(5) control for time fixed effects, column (6) controls both fund and time fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: *CEF Discount*					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Holding_Max(5)	4.838**	5.924***	2.481**	7.906***	3.246***	1.944***
	(2.420)	(2.240)	(0.970)	(2.483)	(0.997)	(0.449)
Pair_Max(5)×CoMax(5)		-1.910***	-1.463***	-1.170**	-1.221***	-0.492***
		(0.325)	(0.391)	(0.468)	(0.412)	(0.124)
CoMax(5)		-0.405	0.159	-0.073	0.240	0.611
		(0.901)	(0.492)	(0.933)	(0.490)	(0.372)
CEF_Max(5)				-6.256***	-1.938**	-1.892***
				(1.895)	(0.781)	(0.681)
Disagreement			0.273		0.290	-0.407
			(0.598)		(0.595)	(0.380)

(Continued)

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	Dependent Variable: *CEF Discount*					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Inve_Price[pos]			-3.875**		-3.805*	0.370
			(1.971)		(1.967)	(1.590)
Inv_Price[neg]			1.211**		1.346***	3.783***
			(0.504)		(0.499)	(1.449)
Div_Yield[pos]			-5.957***		-5.794***	-1.330
			(1.543)		(1.528)	(1.461)
Div_Yield[neg]			-0.803		-0.797	0.684
			(0.641)		(0.632)	(0.731)
Liquidity			-1.098*		-0.947*	0.912*
			(0.562)		(0.561)	(0.487)
Exp_Ratio			-1.362**		-1.224*	0.324
			(0.637)		(0.629)	(0.596)
Holding_Tskew			0.072		0.106	0.384
			(0.401)		(0.393)	(0.481)
Holding_Ivol			-0.270		-0.399	-1.122
			(0.676)		(0.668)	(1.247)
Observations	2,330	2,330	2,330	2,330	2,330	2,330
R-squared	0.200	0.213	0.687	0.262	0.691	0.855

Table 3 Combined M&A Announcement Returns

This table reports coefficient estimates from regressions of combined M&A announcement returns on lottery-like features. The dependent variable is combined cumulative abnormal return (*Combined CAR [−1,+1]*) (expressed in %), where $t = 0$ is the announcement day, or the ensuing trading day if the deal is announced when the market is closed, weighted by the market capitalization of both the acquirer and the target. The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max(3)_A$ and $Max(3)_T$). *Combined_Max(3)* is the average of $Max(3)_A$ and $Max(3)_T$, weighted by their respective market capitalizations in the month prior to the announcement. *CoMax(3)* is the percentage of the top-3 monthly returns that are recorded in the same month. Detailed description of all control variables can be found in the appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. I estimate time-fixed effect 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_Max(3)	-0.990*	-1.280**	-1.268**	-1.729***
	(0.513)	(0.571)	(0.542)	(0.570)
Combined_Max(3)×CoMax(3)			0.624***	0.744***
			(0.189)	(0.186)
CoMax(3)			0.323	0.256
			(0.211)	(0.207)
Disagreement		-0.011		-0.032
		(0.340)		(0.343)
Ln(Acq_MktCap)		-0.894*		-0.902*
		(0.450)		(0.465)
Ln(Acq_MEBE)		-0.013		0.007
		(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)

	Dependent Variable: ***Combined_CAR [−1,+1]***			
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
Ln(Tgt_MktCap)		0.320		0.286
		(0.368)		(0.383)
Ln(Tgt_MEBE)		-0.586**		-0.546**
		(0.246)		(0.247)
Tgt_ROA		-0.039		-0.043
		(0.476)		(0.474)
Tgt_Leverage		0.385		0.351
		(0.226)		(0.231)
Tgt_OCF		-0.011		0.004
		(0.476)		(0.474)
Relative Size		-0.987**		-0.996**
		(0.395)		(0.385)
Tender Offer		0.164		0.169
		(0.207)		(0.204)
Hostile Offer		0.389		0.373
		(0.241)		(0.233)
Competing Offer		-0.078		-0.043
		(0.202)		(0.191)
Cash Only		1.330***		1.288***
		(0.206)		(0.204)
Stock Only		-0.031		-0.071
		(0.295)		(0.294)
Same Industry		0.148		0.098
		(0.170)		(0.181)
Combined_Tskew		-0.173		-0.151
		(0.174)		(0.173)
Combined_Ivol		0.356		0.497
		(0.295)		(0.308)
Observations	1,145	1,145	1,145	1,145
R-squared	0.078	0.174	0.087	0.184

Table 4 Conglomerate Discounts

This table reports coefficient estimates from regressions of conglomerate discounts on measures of lottery-like features. The dependent variable is conglomerate discount, defined as the difference between a conglomerate's *Imputed_MEBE* and its own market-to-book ratio, scaled by *Imputed_MEBE*, where *Imputed_MEBE* is defined as the average *Seg_MEBE* across a conglomerate's segments weighted by this conglomerate's net sales from each segment, and *Seg_MEBE* is defined as the sales-weighted average market-to-book values across single-segment firms within each segment. The lottery-like feature for a firm is proxied by the average top-3 monthly returns within the fiscal year (*Max(3)*). *Cong_Max(3)* is the *Max(3)* from a conglomerate. *Imputed_Max(3)* is defined as the average *Seg_Max(3)* across a conglomerate's segments, weighted by this conglomerate's net sales from each segment, and *Seg_Max(3)* is defined as the sales-weighted average *Max(3)* across five single-segment firms chosen similar to the conglomerate's operation in that segment based on SIC code and sales. $CoMax(3)_{m(i),n(j)}$ is the percentage of top-3 monthly returns that are recorded in the same month for every possible stock pairs *{i,j}* constructed from any two different underlying segments *{m,n}*, and $Pair\_Max(3)_{m(i),n(j)}$ is the average *Max(3)* from these two stocks. $Pair\_Max(3)_{m(i),n(j)}$, $CoMax(3)_{m(i),n(j)}$, and $Pair\_Max(3)_{m(i),n(j)} \times CoMax(3)_{m(i),n(j)}$ are then taken weighted average across all stock pairs and segment pairs (denoted as *Imputed_Max(3)*, *Pair_Max(3)*, and *Pair_Max(3)×CoMax(3)*). Note that after $Pair\_Max(3)_{m(i),n(j)}$ is taken weighted average across all stock pairs and then segment pairs, it equals *Imputed_Max(3)*. All independent variables are standardized to have a mean of zero and a standard deviation of one. I estimate time-fixed effect 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 Discount*				
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Imputed_Max(3)	0.066***	0.097***	0.147***	0.121***	0.173***
	(0.021)	(0.025)	(0.038)	(0.026)	(0.038)
Pair_Max(3)×CoMax(3)		-0.052**	-0.081***	-0.057**	-0.080***
		(0.023)	(0.024)	(0.025)	(0.023)
CoMax(3)		0.044*	0.048**	0.042*	0.047**
		(0.023)	(0.022)	(0.023)	(0.022)
Cong_Max(3)				-0.097***	-0.116***
				(0.020)	(0.019)

(Continued)

(Continued)

	Dependent Variable: *Conglomerate Discount*				
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Disagreement			0.010		0.009
			(0.019)		(0.018)
Ln(Total Asset)			0.047		-0.047
			(0.106)		(0.111)
Ln(Total Asset)2			-0.030		0.031
			(0.111)		(0.114)
Leverage			-0.128***		-0.120***
			(0.024)		(0.024)
Profitability			-0.087***		-0.097***
			(0.023)		(0.022)
Investment Ratio			0.008		0.010
			(0.019)		(0.019)
Imputed_Tskew			-0.037*		-0.040*
			(0.022)		(0.022)
Imputed_Ivol			-0.082***		-0.087***
			(0.030)		(0.030)
Observations	15,907	15,907	15,907	15,907	15,907
R-squared	0.008	0.009	0.030	0.015	0.038

Table 5 Replacing *CoMax* with Non-Max Correlation

This table conducts placebo tests by replacing *CoMax* with *Non_Max_Corr* on CEFs (Panel A), M&A deals (Panel B), and conglomerates (Panel C). In Panel A, the dependent variable is the CEF discount, defined as the difference between a CEF's NAV and its market price, divided by NAV (expressed in %). For each stock pairs among a CEF's top ten holdings, $Non\_Max\_Corr_{i,j}$ is the return correlation excluding top-5 daily returns that are recorded in the same day. All other variables are defined in the same way as in Table 2. $Pair\_Max(5)_{i,j}$, $Non\_Max\_Corr_{i,j}$, and $Pair\_Max(5)_{i,j}\times Non\_Max\_Corr_{i,j}$ are taken weighted average across all stock pairs (denoted as *Holding_Max(5)*, *Non_Max_Corr*, and *Pair_Max(5)×Non_Max_Corr*). I estimate fixed effect regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. In Panel B, the dependent variable is combined cumulative abnormal return (*Combined CAR [−1,+1]*). For each deal, *Non_Max_Corr* is the return correlation excluding top-3 monthly returns that are recorded in the same month. All other variables are defined in the same way as in Table 3. I estimate fixed effect regressions with standard errors (reported in brackets) clustered by time. In Panel C, the dependent variable is conglomerate discount, defined as the difference between a conglomerate's *Imputed_MEBE* and its own market-to-book ratio, scaled by *Imputed_MEBE*. $Non\_Max\_Corr_{m(i),n(j)}$ is the return correlation excluding top-3 monthly returns that are recorded in the same month for every stock pairs *{i,j}* constructed from any two different underlying segments *{m,n}*. All other variables are defined in the same way as in Table 4. $Pair\_Max(3)_{m(i),n(j)}$, $Non\_Max\_Corr_{m(i),n(j)}$, and $Pair\_Max(3)_{m(i),n(j)}\times Non\_Max\_Corr_{m(i),n(j)}$ are taken weighted average across all stock pairs and segment pairs (denoted as *Imputed_Max(3)*, *Non_Max_Corr*, and *Pair_Max(5)×Non_Max_Corr*). I estimate fixed effect regressions with standard errors (reported in brackets) clustered by both firm and time. All independent variables are standardized to have a mean of zero and a standard deviation of one. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Panel A: Closed-end Funds

	Dependent Variable: *CEF Discount*	
VARIABLES	**(1)**	**(2)**
Holding_Max(5)	4.008**	1.837***
	(1.808)	(0.577)
Pair_Max(5)×Non_Max_Corr	-0.593	-0.091
	(0.370)	(0.137)
Non_Max_Corr	-0.598	0.374
	(0.922)	(0.246)
Controls	No	Yes
Observations	2,330	2,330
R-squared	0.133	0.839

Panel B: Mergers and Acquisitions		
	Dependent Variable: ***Combined CAR[−1,+1]***	
VARIABLES	**(1)**	**(2)**
Combined_Max(3)	-1.036*	-1.418**
	(0.505)	(0.522)
Combined_Max(3)×Non_Max_Corr	0.126	0.238
	(0.255)	(0.253)
Non_Max_Corr	0.221	0.251
	(0.218)	(0.205)
Controls	No	Yes
Observations	1,145	1,145
R-squared	0.079	0.176

Panel C: Conglomerates		
	Dependent Variable: ***Conglomerate Discount***	
VARIABLES	**(1)**	**(2)**
Imputed_Max(3)	0.059***	0.118***
	(0.021)	(0.032)
Pair_Max(3)×Non_Max_Corr	0.054	0.031
	(0.034)	(0.032)
Non_Max_Corr	-0.024	-0.009
	(0.031)	(0.027)
Controls	No	Yes
Observations	15,907	15,907
R-squared	0.009	0.037

Table 6 Alternative Proxies for Lottery-like Features

This table reports robustness tests for CEFs (Panel A), M&A deals (Panel B), and conglomerates (Panel C), using alternative proxies for lottery-like features. In Panel A, I consider the average top-2/3 daily returns within a month and top-60 daily returns within a year (denoted as *Max(i), i*=2,3, or 60). I report coefficient estimates from regressions of CEF discounts on these alternative measures. The dependent variable is the CEF discount, defined as the difference between a CEF's NAV and its market price, divided by NAV (expressed in %). *CEF_Max(i)*, *Holding_Max(i)*, *CoMax(i)*, and *Pair_Max(i)×CoMax(i)* are defined in the same way as in Table 2, except that the top-*i* daily returns are used to compute these variables. I estimate fixed effect regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. In Panel B, I consider three alternative proxies for lottery-like features: (1) the average top-5 monthly returns with 24 months prior to the announcement; (2) the average top-12 weekly returns within a year prior to the announcement; (3) the average top-60 daily returns with in a year prior to the announcement. I report coefficient estimates from regressions of combined M&A announcement day returns on these three alternative proxies. The dependent variable is combined cumulative abnormal return (*Combined CAR [−1,+1]*). *Combined_Max(i)*, *CoMax(i)*, and their interactions (*i* = 5,12,60) are defined in the same way as in Table 3, except that top-5 monthly returns/top-12 weekly returns/top-60 daily returns are used to compute these variables. I estimate fixed effect regressions with standard errors (reported in brackets) clustered by time. In Panel C, I consider three alternative proxies for lottery-like features: (1) the average top-5 monthly returns with 24 months; (2) the average top-12 weekly returns within a year; (3) the average top-60 daily returns with in a year. I report coefficient estimates from regressions of conglomerate discounts on these alternative proxies. The dependent variable is conglomerate discount, defined as the difference between a conglomerate's *Imputed_MEBE* and its own market-to-book ratio, scaled by *Imputed_MEBE*. *Imputed_Max(i)*, *Cong_Max(i)*, *CoMax(i)*, and *Pair_Max(i)×CoMax(i)* are defined in the same way as in the main results (*i* = 5,12,60), except that top-5 monthly returns/top-12 weekly returns/top-60 daily returns are used to compute these variables. I estimate fixed effect regressions with standard errors (reported in brackets) clustered by both firm and time. Detailed description of control variables from all panels can be found in the appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Closed-end Funds					
VARIABLES	**(1)**	**VARIABLES**	**(2)**	**VARIABLES**	**(3)**
Holding_Max(2)	1.138**	*Holding_Max(3)*	1.655***	*Holding_Max(60)*	2.338**
	(0.459)		(0.416)		(1.049)
Pair_Max(2)×CoMax(2)	-0.233**	*Pair_Max(3)×CoMax(3)*	-0.425**	*Pair_Max(60)×CoMax(60)*	-0.788**
	(0.096)		(0.201)		(0.313)
CoMax(2)	0.468	*CoMax(3)*	0.528*	*CoMax(60)*	-0.338
	(0.305)		(0.318)		(0.432)
Controls	Yes	Controls	Yes	Controls	Yes
Observations	2,330	Observations	2,330	Observations	2,330
R-squared	0.865	R-squared	0.854	R-squared	0.856

Panel B: Mergers and Acquisitions					
VARIABLES	**(1)**	**VARIABLES**	**(2)**	**VARIABLES**	**(3)**
Combined_Max(5)	-1.998***	*Combined_Max(12)*	-2.526**	*Combined_Max(60)*	-2.639**
	(0.530)		(0.962)		(1.035)
Combined_Max(5)×CoMax(5)	0.907***	*Combined_Max(12)×CoMax(12)*	1.541**	*Combined_Max(60)×CoMax(60)*	1.479*
	(0.212)		(0.708)		(0.856)
CoMax(5)	0.300	*CoMax(12)*	-0.347	*CoMax(60)*	-0.482
	(0.218)		(0.404)		(0.439)
Controls	Yes	Controls	Yes	Controls	Yes
Observations	1,145	Observations	1,145	Observations	1,145
R-squared	0.186	R-squared	0.174	R-squared	0.17

(Continued)

(Continued)

Panel C: Conglomerates					
VARIABLES	**(1)**	**VARIABLES**	**(2)**	**VARIABLES**	**(3)**
Imputed_Max(5)	0.148***	*Imputed_Max(12)*	0.185***	*Imputed_Max(60)*	0.244***
	(0.043)		(0.048)		(0.072)
Pair_Max(5)×CoMax(5)	-0.068***	*Pair_Max(12)×CoMax(12)*	-0.090***	*Pair_Max(60)×CoMax(60)*	-0.114***
	(0.026)		(0.025)		(0.032)
CoMax(5)	0.045*	*CoMax(12)*	0.039*	*CoMax(60)*	0.014
	(0.025)		(0.020)		(0.027)
Controls	Yes	Controls	Yes	Controls	Yes
Observations	15,907	Observations	15,907	Observations	15,907
R-squared	0.035	R-squared	0.032	R-squared	0.029