Offsetting Disagreement and Security Prices*

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Abstract

Portfolios often trade at substantial discounts relative to the sums of their components (e.g., closed-end funds). We propose a simple, unifying explanation for this phenomenon: Investors often disagree about the value of each individual component; as long as investors' *relative* views are not perfectly and positively correlated across components ("investor beliefs cross"), disagreement partially offsets at the portfolio level. That is, investors generally disagree less at the portfolio level than at the individual component level. In the presence of short-sale constraints, wherein prices are set by the most optimistic investors, high disagreement comes with high price levels. Our proposed channel of "belief crossing" thus provides an explanation for why portfolios often trade below the sums of their parts. Utilizing closed-end funds, exchange-traded funds, mergers and acquisitions, and conglomerates as settings where prices of the underlying components and the price of the aggregate portfolio can be separately evaluated, we present evidence supportive of our argument.

JEL Classification: G11, G12, G14, G20

Keywords: Investor Disagreement, Belief-Crossing, Portfolio Discounts

1. Introduction

We propose that in financial markets the whole generally trades at a discount relative to the sum of its parts. The reason is that companies liked by some investors are often not liked by other investors. This makes it almost impossible to construct a portfolio that perfectly pleases large investor groups and contains only every investor's most favorite companies. The maximum level of excitement that a portfolio of companies generates among investors is, therefore, almost always lower than the combined level of excitement that the individual companies in the portfolio generate among their most fervent supporters. In the presence of short-sale constraints, wherein prices are set by the most optimistic investors, this discrepancy in the maximum level of excitement becomes priced and the portfolio trades at a discount relative to its underlying assets.

To illustrate this proposal with a simple example, imagine two investors and two firms, Apple and Microsoft. The first investor is enthusiastic about Apple (perceived value = \$10), but not excited about Microsoft (perceived value = \$5). The valuations are reversed for the second investor, who is excited about Microsoft (perceived value = \$10), but not excited about Apple (perceived value = \$5). In the presence of binding short-sale constraints, market prices reflect the valuations of the most bullish investors, so the market values of Apple and Microsoft are \$10 each. If Apple and Microsoft were combined and traded "as a package," however, no investor would be willing to pay more than \$15 for Apple and Microsoft combined. This is because "investors' beliefs cross:" Apple is liked by the first investor but not by the second investor; Microsoft is liked by the second investor but not by the first investor. "Apple-soft," which holds no particular appeal to any investor group, therefore trades at a discount relative to the sum of its components.

The difference in the maximum level of excitement between the whole and the sum of its parts widens with the interaction between disagreement and belief-crossing (hereafter referred to as *embedded belief-crossing*). That is, for there to be a wedge in the maximum level of excitement between the whole and the sum of its parts, we simultaneously need both investor disagreement and belief crossing. If investors hold similar views about the value of each asset (e.g., valuing Apple at $7.55 while valuing Microsoft at $7.45), the fact that investor beliefs cross is of little practical consequence. Similarly, if investor beliefs do *not cross* and an investor group is excited about both Apple and Microsoft, that same investor group will also be excited about "Apple-soft." The level of enthusiasm that the whole ("Apple-soft") generates amongst its most fervent supporters will therefore be the same as the combined maximum levels of enthusiasm that the parts receive (Apple and Microsoft).

The main setting we exploit to empirically assess the validity of our argument is that of US equity closed-end funds (CEFs) and US equity exchange-traded funds (ETFs). CEFs are corporations holding portfolios of stocks. Both CEFs and their holdings are traded on stock exchanges. Based on our proposed mechanism, if a CEF holds assets with a high level of embedded belief-crossing, that CEF should trade at a discount relative to the sum of the values of the CEF's underlying assets.

Motivated by prior studies, we approximate investor beliefs via quarterly earnings forecasts issued by brokerage firms. We conjecture that disagreement over a given stock across brokerages, as well as belief-crossing for a pair of stocks across brokerages, provide useful information about the level of disagreement and belief-crossing that is present among investors.

For any given pair of stocks held by a CEF, we compute the average dispersion in earnings forecasts across the two stocks and augment it with information about whether the brokerage with the most optimistic earnings forecasts for the first stock tends to issue the most pessimistic earnings forecasts for the second. The resulting variable, *PairwiseCov*, is such that a large positive realization implies a high level of embedded belief-crossing. We then aggregate pairwise *PairwiseCov* to the portfolio level, *InvCov*, defined as the portfolio-weighted average *PairwiseCov*.

The average CEF in our sample holds around one hundred stocks. In our main analysis, we compute our measure of embedded belief-crossing among a fund's largest ten holdings. As we discuss in Section 3.5, our focus on the top ten, which account for a substantial portion of the total portfolio value, greatly helps reduce the dimensionality of the data and bring the calculation to a manageable level. Our focus on the top ten also has intuitive appeal as retail investors, who are the primary shareholders of CEFs and ETFs, are more likely to gauge their level of excitement about a fund based on its top-ten holdings than its full holdings: The former is readily observable on a fund's website and factsheet, as well as from financial information aggregators such as Morningstar. Obtaining information on a fund's full holdings, on the other hand, requires investors to study reports or regulatory filings from the Securities and Exchange Commission's (SEC) Edgar server.[1]

Consistent with our prediction, we find that greater embedded belief-crossing among a CEF's underlying assets comes with larger CEF discounts. Our panel regression of CEF premia on *InvCov* and a host of controls produces an estimate for *InvCov* of -0.491

[1] Having said all this, as we discuss in Section 3.5, our results are robust to including stocks outside of a fund's top ten.

(t-statistic = -2.68), suggesting that a one-standard-deviation increase in *InvCov* comes with a 0.49% increase in the CEF discount. For reference, the average CEF discount in our sample is 4.3%. Consistent with short-sale constraints playing an important role in generating our findings, our embedded belief-crossing effect strengthens with estimates of how short-sale constrained the corresponding CEF's underlying assets are.

We make analogous observations for ETFs. ETFs are investment companies holding portfolios of securities, whereby both ETFs and their holdings are traded on stock exchanges. The market value of an ETF, like that of a CEF, can deviate from the sum of the values of its underlying assets, although the magnitude of this disparity is much smaller for ETFs than for CEFs due to the presence of authorized participants, who can create and redeem large blocks of an ETF's underlying holdings.

Employing an empirical design similar to the one we use for CEFs, we find that ETF discounts increase with the level of embedded belief-crossing.[2] In particular, our results suggest that a one-standard-deviation increase in *InvCov* leads to a 1.5bps (t-statistic = 2.24) increase in the ETF discount. Compared with the median ETF discount of 2bps in our sample, such a rise essentially translates into a doubling of the ETF discount. Again, our effect strengthens with estimates of how short-sale constrained the corresponding ETF's underlying assets are.

For ETFs, our mechanism yields an additional prediction. An increase in embedded belief-crossing increases the discount of the ETF share relative to the value of the underlying assets. This should induce authorized participants to buy ETF shares in the

[2] We exclude from our sample ETFs that track broad market indices (e.g., S&P 500, Russell 1000, Russell 2000, Wilshire 4500, Wilshire 5000), as investors in these ETFs are simply tracking the market and unlikely to pay much attention to the portfolio composition.

secondary market, redeem them for the underlying holdings, and sell these holdings to lock in a gain. Such a process amounts to capital flowing out of an ETF. Corroborating this prediction, we find that a one-standard-deviation increase in *InvCov* is associated with a 0.38% (t-statistic = 3.05) increase in monthly ETF outflows. For reference, the average monthly ETF flow in our sample is 1.6%.

In additional tests, we also consider mergers and acquisitions (M&As) and conglomerate firms. The combined announcement day return of an acquirer and a target in part reflects the difference between the value of the joint firm (i.e., "the portfolio value") and the sum of the values of the acquirer and target operating separately (i.e., "the sum of the individual component values"). If embedded belief-crossing lowers the value of the whole relative to the sum of its parts, embedded belief-crossing across acquirer and target should lower the combined announcement day return.

Consistent with this prediction, our regression of combined announcement day returns on *InvCov* produces an estimate for *InvCov* of -1.713 (t-statistic = -4.72), suggesting that a one-standard deviation increase in *InvCov* is followed by 1.713% lower combined announcement day returns. This result easily survives the inclusion of a range of variables known to forecast M&A combined announcement day returns.[3]

Relatedly, conglomerates are corporations operating in multiple industry segments. To the extent that investor excitement differs by industry, the valuation ratio of a conglomerate should fall below that of its single-industry counterparts.[4] Consistent with

[3] Duffie, Garleanu and Pedersen (2002) employ a similar argument to explain the higher (seemingly excessive) valuation of equity carve-outs relative to a parent company during the NASDAQ bubble.

[4] As we discuss in Section 3.5.3, we are unable to construct a measure of belief-crossing for conglomerates.

this prediction, we find that a conglomerate's "diversification discount" increases with disagreement about a conglomerate's underlying industry segments.

2. Literature and Contribution

Our primary contribution comes from our novel observation that investor beliefs sometimes cross, which, combined with short-sale constraints, can lead the whole to trade at a discount relative to the sum of its parts. Our evidence suggests that this relatively "innocent" point can help explain well-known price patterns of assets ranging from CEFs and ETFs to firms engaging in M&As to conglomerates. In general, our framework should be applicable to any situation involving portfolios of companies or large companies operating in multiple segments.[5]

We also shed light on the applicability of a prominent behavioral framework—that of disagreement models—and the relevance of a much-debated source of market friction—that of short-sale constraints. At their core, disagreement models presume that investor beliefs are correct, on average, but that investors often agree to disagree (due to, for example, overconfidence). In addition, some investors cannot or will not sell short (Miller, 1977; Duffie, Garleanu, and Pedersen, 2002; Scheinkman and Xiong, 2003; Hong and Stein, 2007). In other words, some investors do not bet against perceived overvaluation, but rather sit out of the market. Since, in this setting, market prices are determined by optimists, prices are generally upward biased. Moreover, prices rise further if optimists become more optimistic, even if at the same time pessimists become more pessimistic.

[5] In contemporaneous and subsequent work, Bhandari (2016) and Reed, Saffi and Van Wesep (2016) provide evidence that offsetting disagreement helps explain corporate spinoff announcement day returns and conglomerate firm discounts.

That is, holding investors' average beliefs constant, the upward bias in stock prices increases with the level of investor disagreement.

Subsequent work assessing this prediction finds that stocks with higher analyst earnings-forecast dispersion and those experiencing reductions in mutual fund ownership breadth (which means more investors sitting out of the market) indeed earn lower future abnormal returns (Diether, Malloy and Scherbina, 2002; Chen, Hong and Stein, 2002).

While the existing evidence is consistent with models of investor disagreement and short-sale constraints, alternative interpretations remain. For example, investors tend to disagree to a greater extent regarding firms with many growth opportunities than regarding firms with mostly assets in place. Thus, one may argue that it is the exercise of growth options, rather than investor disagreement, which leads to the observed lower future returns (Johnson, 2004). In addition, investors tend to disagree to a greater extent when there is greater valuation uncertainty (e.g., during the tech bubble), which also strengthens the effect of other behavioral biases, such as over-optimism (Einhorn, 1980; Hirshleifer, 2001). Over-optimism can lead, in turn, to higher current valuation and lower future returns.[6] In addition, a growing body of work (e.g., Asquith, Pathak and Ritter, 2005; Boehmer, Jones and Zhang, 2008; Kaplan, Moskowitz and Sensoy, 2013) argues that few stocks are meaningfully short-sale constrained and that the practical relevance of short-sale constraints should be questioned altogether.

In this paper, we re-assess the disagreement framework and the relevance of short-sale constraints by deriving an implication that is unique to the disagreement/short-sale

[6] This argument is often viewed as a possible explanation for the NASDAQ bubble. Investors became overly optimistic about Internet firms' future prospects partly because these firms suffered from high valuation uncertainty.

constraint framework. In particular, we note that when investor beliefs cross, it is impossible to construct a portfolio that perfectly pleases large groups of investors and contains only every investor's most favorite companies. By the same token, it is also impossible to construct a portfolio that includes only every investor's least favored companies. The level of investor disagreement at the portfolio level is therefore always lower than the level of investor disagreement at the individual component level. Put differently, even if investors disagree strongly about the value of individual components, as long as their relative views are not perfectly and positively correlated across these components, disagreement partially offsets at the aggregate portfolio level.

Our empirical strategy, then, is to compare two assets, an aggregate portfolio and the portfolio's underlying components. Both are nearly identical in terms of growth options, investor optimism, and other characteristics, yet they differ strongly along the dimension of investor disagreement: The aggregate portfolio tends to exhibit low investor disagreement, whereas the underlying components tend to exhibit high investor disagreement. As such, our approach provides a relatively clean and powerful setting in which to test the relevance of investor disagreement and short-sale constraints in determining asset prices.

3. Data and Variables

In this section, we introduce our CEF setting (Section 3.1), our ETF setting (Section 3.2), our M&A setting (Section 3.3) and our conglomerates setting (Section 3.4). We discuss our embedded belief-crossing variable in Section 3.5.

3.1 Closed-End Funds

CEFs are publicly traded companies. Rather than using the proceeds from an initial public offering (IPO) and subsequent seasoned equity offerings to invest in physical assets, these companies acquire portfolios of equity securities. Because a CEF itself is traded on a stock exchange, we can compare the market value of a given CEF against the market value of its underlying holdings.

We include in our sample US equity closed-end funds with sufficient available data to construct the CEF premium and our embedded belief-crossing variable along with the following control variables: *Inverse Price*, *Dividend Yield, Liquidity Ratio*, *Expense Ratio*, *Excess Idiosyncratic Volatility*, and *Excess Skewness*. We describe how we construct the CEF premium and our embedded belief-crossing variable below. We discuss the controls in Appendix Table A1. For ease of interpretation, all independent variables in our regression analysis are normalized to have a standard deviation of one.

We identify CEFs via share codes 14 and 44 in the CRSP database. We obtain CEF price and net asset value (NAV) data from CRSP and COMPUSTAT, respectively. The CEF holdings are from Morningstar. Most of the data for the controls come from Lipper. Our final sample contains 85 CEFs over the 2002–2014 period. Our sample period is determined by the availability of CEF data provided by LIPPER and MORNINSTAR.[7]

Quarterly CEF premia are calculated as follows:

$$Premium_{i,t}=\frac{Price_{i,t}\text{-}NAV_{i,t}}{NAV_{i,t}}. \tag{1}$$

While price and NAV data are available at a higher frequency, we measure the CEF discount at the quarterly frequency to match the frequency of our dependent variable

[7] Following Chan, Jain, and Xia (2008), we exclude data for the first six months after a fund's IPO and for the month preceding the announcement of liquidation or open-ending to "avoid distortions associated with the flotation and winding up of closed-end funds" (p. 383).

with that of our embedded belief-crossing variable, which, as we discuss in Section 3.5, can be computed only on a quarterly basis. As shown in Table 1, the average CEF discount in our sample is 4.3%, with a standard deviation of 15.0%. These figures are similar to those reported in prior studies (e.g., Bodurtha, Kim, and Lee, 1995; Klibanoff, Lamont, and Wizman, 1998; Chan, Jain, and Xia, 2008; Hwang, 2011).

3.2 Exchange-Traded Funds

ETFs are similar to CEFs in that both the ETF and the ETF's underlying holdings are traded separately on stock exchanges. The market value of an ETF sometimes differs from the combined value of its underlying assets, although the magnitude of this disparity is much smaller for ETFs than for CEFs due to the presence of authorized participants.

We include in our sample US equity exchange-traded funds with sufficient available data to construct the quarterly ETF premium and the same set of quarterly independent variables as in the CEF setting. We exclude from our sample ETFs that track broad market indices (e.g., S&P 500, Russell 1000, Russell 2000, Wilshire 4500, Wilshire 5000),[8] as investors in these ETFs are merely tracking the market and probably do not pay much attention to the portfolio composition. Following Da and Shive (2016), we obtain ETF price and NAV data from CRSP; we identify ETFs via share code 73. The ETF holdings data are also from CRSP. Most of the data for the controls come from Lipper. We have data available from 2003 through 2014 and our sample contains 461 ETFs.

As reported in Table 1, the mean (median) ETF discount in our sample is 0.47 bps (1.96 bps) with a standard deviation of 36.15 bps. These figures are in line with those

[8] The full list of indices is available upon request.

reported in prior research on ETF discounts (e.g., Petajisto, 2013). While the discount is small in percentage terms, given the size of the ETF industry, it is large in dollar terms.

3.3 Mergers and Acquisitions

Our M&A sample includes M&A deals with sufficient available data to construct the *Combined Announcement Day Return*, our embedded belief-crossing variable as well as acquirer and target market capitalization, market-to-book ratio, return on assets (ROA), leverage, operating cash flows, and governance. We also require data to construct *Combined Idiosyncratic Volatility*, *Combined Skewness*, *Same Industry*, *Relative Size*, *Tender Offer*, *Hostile Offer*, *Competing Offer*, *Cash Only*, and *Stock Only*. We describe how we construct *Combined Announcement Day Return* and our embedded belief-crossing variables below. We discuss the controls in Appendix Table A1. Again, all independent variables in our regression analysis (with the exception of a few categorical variables) are normalized to have a standard deviation of one. Our data sources are SDC, CRSP, and COMPUSTAT, and our sample period runs from 1989 through 2014. After applying the above screening criteria, we arrive at a sample of 405 M&As.

Combined Announcement Day Return is the average cumulative abnormal return over days [-1,+1] across an acquirer and a target, weighted by their market capitalization in the month prior to an announcement:

$$CAR(-1,1) = w_A * CAR(-1,1)_A + w_T * CAR(-1,1)_T, \qquad (2)$$

where t=0 is the day of the M&A announcement (or the ensuing trading day). Following prior literature, we use DGTW adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) to compute *CAR*. As reported in Table 1, the average combined announcement day return in our sample is 2.1%; the standard deviation is 7.0%.

3.4 Conglomerate Firms

Conglomerates are firms operating in multiple industry segments. Our conglomerate sample consists of all firms that possess sufficient available data to construct the "diversification discount" variable and the following normalized independent variables: *Disagreement*, *Number of Segments*, *Total Assets*, *Leverage*, *Profitability*, *Investment Ratio*, *Excess Idiosyncratic Volatility*, and *Excess Skewness*. We describe how we construct the diversification discount and disagreement variables below. We discuss the controls in Appendix Table A1. Our data sources are CRSP and COMPUSTAT. Our final sample spans the period 1984–2014 and contains 2,792 conglomerates.

The diversification discount is the difference between a conglomerate's market-to-book ratio (*MB*) and its imputed *MB* (defined below), scaled by the latter.

$$Premium_{i,t}=\frac{MB_{i,t} - Imputed\ MB_{i,t}}{Imputed\ MB_{i,t}}. \tag{3}$$

When computing *MB*, we use information for June of calendar year t to compute the market value of equity and we use accounting data for fiscal year t-1 to compute the book value of equity. To construct the imputed *MB*, we first compute the average *MB* for each two-digit SIC-code industry, *Industry-MB*, whereby we use only single-segment firms that are from the same market capitalization tercile as the conglomerate. The imputed *MB* is the sales-weighted average *Industry-MB* across conglomerate i's segments as of t. Following prior studies, we winsorize our variable at the 1st and 99th percentiles. As reported in Table 1, the average conglomerate discount in our sample is 14.9%, which, again, is in line with figures reported in prior research (Berger and Ofek, 1995; Lamont and Polk, 2001; Mitton and Vorkink, 2010).

3.5 Embedded Belief-Crossing for CEFs, ETFs, M&As, and Conglomerates

To empirically assess our mechanism, we require both a measure of investor disagreement and a measure of investor belief-crossing for each pair of stocks. Our study approximates investor beliefs via analysts' earnings forecasts. One concern regarding this approach is that *analyst* disagreement and *analyst* belief-crossing do not represent *investor* disagreement and *investor* belief-crossing. A more technical challenge is that the typical CEF or ETF portfolio is highly diversified. Yet, to construct our belief-crossing variable, we need a pair of stocks to be covered by at least two common analysts; in practice, most analysts focus on stocks from only one or two industries.

We address both concerns by computing our measures at the *brokerage* level.[9] Constructing our measures at the brokerage level has two advantages. Consider the following example:

	Stock A	Stock B
Analyst 1 (Morgan Stanley)	1 (most optimistic)	
Analyst 2 (Morgan Stanley)		1 (most optimistic)
Analyst 3 (Goldman Sachs)	2 (most pessimistic)	2 (most pessimistic)

Given that most investors deal with a small number of brokers for trade execution, it is plausible that some investors rely more heavily on some brokerage firms than others for information. In the above example, Morgan Stanley is always more optimistic than Goldman Sachs so it is conceivable that investors paying more attention to Morgan Stanley's sell-side research also will be more optimistic than investors paying more attention to Goldman Sachs' research. If so, disagreement and belief-crossing measured at

[9] For robustness checks, we re-run our analyses using analyst-level measures and we find similar results.

the brokerage level provides useful information about the level of disagreement and belief-crossing that exists among investors. Our focus on brokerages also facilitates the construction of the belief-crossing variable, as brokerage firms tend to cover a wide range of stocks through the simultaneous employment of multiple analysts.

Note that we need not take a stand on the direction of the information flow, i.e., the degree to which information flows from brokerages to investors and vice versa. If brokerages impact investors' beliefs, then brokerage-level opinions naturally translate to investor-level opinions. Even if brokerages are merely broadcasting the views of their various clients, the belief structure measured at the brokerage level remains a reflection of the belief structure among investors.

Note further that we do not require investors holding underlying assets to be identical to the investors holding a portfolio of those assets. As long as the various investor groups rely, to some degree, on the reports produced by brokerages, the level of belief-crossing at the brokerage level provides useful information regarding the level of belief-crossing in the overall investor population. As such, it matters less to the interpretation of our results that not all investors hold the same assets.[10]

3.5.1 Disagreement and Crossing – CEFs and ETFs

Our main analysis pertaining to CEFs and ETFs is based on CEFs'/ETFs' quarterly top-ten holdings. Each CEF/ETF in each year-quarter t produces 45 possible top-ten stock pairs (=n*(n-1)/2). The number of possible stock pairs increases exponentially with the

[10] In additional tests, we re-estimate our primary regression equations for the subset of observations for which a CEFs' (an ETFs') underlying assets are held primarily by retail investors. That is, we focus on a subset of observations for which there is greater overlap between investors pricing the underlying assets and investors pricing the overall portfolios. Our results are virtually unchanged.

number of stocks considered. While there are 45 possible stock pairs across the top ten stocks, there are 1,225 possible stock pairs across 50 stocks. The average CEF holds 97 stocks (→ 4,656 possible stock pairs); the 90th percentile is 200 stocks (→ 19,900 possible stock pairs). The average ETF holds 255 stocks (→ 32,385 possible stock pairs); the 90th percentile is 623 stocks (→ 193,753 possible stock pairs). Focusing on the top ten holdings therefore dramatically reduces the dimensionality of the data and helps bring the calculation to a manageable level.

Focusing on top-ten holdings also has intuitive appeal: The top-ten holdings of CEFs and ETFs are readily available through investment sites such as Morningstar, Yahoo Finance, the CEF Center, or the ETF Database; they are also readily available from a fund's website and a fund's factsheet.[11] Obtaining information on full holdings, on the other hand, requires going through a fund's reports or downloading regulatory filings from the SEC's Edgar server. Because of this friction, we believe that retail investors (the main shareholders in CEFs and ETFs) are more likely to assess the appeal of a portfolio based on its top-ten holdings rather than its entire portfolio holdings.[12]

We start by computing the pairwise embedded belief-crossing for each stock pair *j,l* covered by at least two common brokerage houses. In particular, we first compute the price-scaled earnings forecast dispersion for both stock *j* and stock *l*:

$$Dispersion_{j\ or\ l} = \frac{StDev\left(Forecast(EPS)_{h,j\ or\ l}\right)}{P_{j\ or\ l}}, \tag{4}$$

[11] To illustrate, Online Appendix Figure A1 contains a screenshot of Gabelli Equity Trust, one of the largest equity CEFs by assets under management.

[12] To assess the robustness of our findings, we also experiment with other portfolio cutoffs. As shown in Online Appendix Table A1, our results remain economically and statistically significant if we instead compute embedded belief-crossing based on the top 20, 30, 40, or 50 stocks.

where $Forecast(EPS)_{h,j\ or\ l}$ is brokerage h's most recent forecast for quarterly earnings-per-share. Because each brokerage firm assigns only one of its analysts to cover a stock, brokerage earnings forecast dispersion is equivalent to analyst earnings forecast dispersion. (However, brokerage-level belief-crossing is *not* equivalent to analyst-level belief-crossing.) We require that forecasts be made in the ninety-day period prior to the corresponding earnings announcement date and the corresponding earnings announcement date to fall within the ninety-day period prior to the corresponding portfolio holdings report date. P_j is the price-per-share for firm j as of the end of the corresponding fiscal quarter. We winsorize *Dispersion* at the 99$^{\text{th}}$ percentile.

We compute *Disagreement* as the portfolio-weighted average dispersion across stock j and stock l:

$$Disagreement = w_j Dispersion_j + w_l Dispersion_l. \quad (5)$$

In the next step, we draw from the list of brokerage houses that cover both stock j and stock l and compute the Spearman rank correlation in earnings forecasts between these two stocks, multiplied by negative one:

$$Crossing = Corr\left(Forecast\left(EPS_j\right), Forecast\left(EPS_l\right)\right) * (-1).$$

(6)

When the most optimistic investor in the first stock is also the most optimistic investor in the second stock ("no belief-crossing"), the correlation gravitates towards positive one and the *Crossing* variable gravitates towards negative one. In contrast, when the most optimistic investor in the first stock is the most pessimistic investor in the second stock ("perfect belief-crossing"), the correlation gravitates towards negative one and the

Crossing variable gravitates towards positive one. A value of *Crossing* between minus one and plus one indicates some degree of belief crossing.

Recall that our mechanism is a joint effect of *both* investor disagreement and investor belief-crossing. Our main independent variable then is the interaction of investor disagreement with investor belief-crossing, *PairwiseCov*:

$$PairwiseCov(j,l) = Disagreement_{j,l} * Crossing_{j,l}. \tag{7}$$

In our final step, we aggregate pairwise *PairwiseCov* to the portfolio level, defined as the portfolio-weighted average *PairwiseCov* across all 45 stock pairs (*j, l*):

$$InvCov = \frac{\sum_{j,l}(w_j + w_l) * PairwiseCov(j,l)}{\sum_{j,l}(w_j + w_l)} \tag{8}$$

A large positive realization of *InvCov* implies a high level of embedded belief-crossing.[13]

3.5.2 Disagreement and Crossing – M&As

The construction of our embedded belief-crossing variable is similar for M&As. For a given M&A, we compute the price-scaled earnings forecast dispersion for both the acquirer and the target, winsorized at the 99th percentile. We compute *Disagreement* as the average dispersion across the acquirer and the target, weighted by the acquirer's and the target's market capitalization in the month prior to the announcement. We draw from the list of brokerage houses that cover both the acquirer and the target prior to the M&A announcement date and compute the Spearman rank correlation in earnings forecasts

[13] Note that the portfolio average *InvCov* in equation (8) does not necessarily equal the product of the portfolio average *Disagreement* or the portfolio average *Crossing*, as *Disagreement* and *Crossing* may be correlated across stock pairs. We have also worked with an alternative specification of *PairwiseCov*, in which *Disagreement* is defined as the product of the two dispersions, rather than the weighted average. The results are by and large unchanged.

between the acquirer and the target, multiplied by negative one. Our main independent variable, *InvCov*, is the interaction of *Disagreement* with investor belief-crossing.

3.5.3 Disagreement – Conglomerates

As in the previous settings, we rely on price-scaled earnings forecast dispersions to approximate investor disagreement for conglomerates. We first focus on single-segment firms that are in the same size tercile as the conglomerate to compute the average forecast dispersion for each two-digit SIC-code industry as of t (we again winsorize *Dispersion* at the 99$^{\text{th}}$ percentile.) We then compute $Disagreement_{i,t}$ as the sales-weighted average industry-level dispersion across all segments in which conglomerate i operates as of year t. Given that analysts/brokerages do not issue industry-level forecasts, we cannot compute belief-crossing for conglomerates. The conglomerates setting therefore only produces indirect evidence of our here proposed mechanism.

Recall that, when calculating $Premium_{i,t}$, we use information for June of calendar year t to compute the market value of equity and use accounting data from fiscal year t-1 to compute the book value of equity. To line up the timing of our dependent and independent variables, earnings forecasts used to construct $Disagreement_{i,t}$ are for annual earnings of fiscal year t-1 (which must be reported by June of year t).

4. Main Results

Our main analysis is based on CEFs and ETFs. We estimate a pooled OLS regression with fund and year-quarter fixed effects. We do so separately for CEFs and ETFs. The dependent variable is the CEF premium (%) or the ETF premium (bps), measured at a quarterly frequency. The independent variables include *InvCov* and the controls described in Section 3.1. *T*-statistics are based on standard errors clustered by both fund and year-quarter.

Table 2 presents the results for CEFs. As shown in Column 1 and consistent with our prediction, the coefficient estimate for *InvCov* is -0.491 (t-statistic = -2.68), implying that a one-standard-deviation increase in *InvCov* leads to a 0.49% increase in the CEF discount. For reference, the average CEF discount in our sample is 4.3%.

Based on our framework, the embedded belief-crossing effect should strengthen with the degree to which stocks are short-sale constrained. To test this prediction, we approximate short-sale constraints via the fraction of shares held by institutions. Institutional ownership is positively related to the supply of lendable shares (Nagel, 2005), any increase in which eases short-sale constraints. Following prior studies (e.g., Hong, Lim and Stein, 2000), we orthogonalize institutional ownership with respect to market capitalization by estimating cross-sectional regressions of the fractions of shares held by institutions on the natural logarithm of market capitalization and by saving the residuals (*IO*). We then embed (1–*IO*) into *InvCov*. Specifically, we multiply *Dispersion* by (1-*IO*) for each stock; we then follow the same procedure outlined in Section 3.5.1. A large positive realization of this variable indicates that there is a high level of embedded belief-crossing and a high level of short-sale constraints.

In additional tests, we further interact (1-*IO*) with the level of short interest (*SI*) as stocks with low supplies of lendable shares and high demand for shorting are perhaps the most costly to short and, therefore, the most short-sale constrained (Asquith, Pathak and Ritter, 2005).[14] We then embed (1–*IO*)**SI* into *InvCov*. Again, a large positive

[14] Short interest is the number of shares shorted divided by the number of shares outstanding.

realization of this variable indicates that there is a high level of embedded belief-crossing and a high level of short-sale constraints.

The results are presented in Columns 2 and 3 of Table 2. In short, we find that our results become stronger when augmenting our measure of embedded belief-crossing with (1-*IO*) or (1-*IO*) * *SI*. In Column 2, the coefficient estimate for *InvCov*, which takes into account (1-*IO*), increases to -0.567 (*t*-statistic = -2.61). In Column 3, the coefficient estimate for *InvCov*, which takes into account (1-*IO*) * *SI*, becomes -0.499 (*t*-statistic = -2.48).

A few notes on the coefficient estimates for the control variables: The negative estimate for $InversePrice_{neg}$ suggests that prices are further away from NAVs for low-priced CEFs, perhaps, as these CEFs face greater limits to arbitrage (Pontiff 1996). The positive estimate for *Liquidity Ratio* suggests that CEFs trade at more of a premium (or less of a discount) if shares of CEFs are more liquid than those of the corresponding underlying assets, which is consistent with Cherkes, Sagi and Stanton (2008).

Table 3 presents the results for ETFs. As reported in Column 1 of Table 3, the coefficient estimate for *InvCov* is -1.465 (*t*-statistic = -2.24), indicating that a one-standard-deviation increase in *InvCov* leads to a 1.5bp increase in the ETF discount. Compared with the median ETF discount of 2bps in our sample, such a rise essentially translates into a doubling of the ETF discount. Similar to what we observe for CEFs, when augmenting our measure of embedded belief-crossing with (1-*IO*), the coefficient estimate for *InvCov* increases to -1.697 (*t*-statistic = -2.41). When augmenting our measure of embedded belief-crossing with (1-*IO*) * *SI*, the coefficient estimate for *InvCov* increases further to -1.744 (*t*-statistic = -2.54).

Together, our result that portfolios trade at greater discounts the more embedded beliefs cross and the more short-sale constraints are binding is strongly consistent with our overall framework.

4.1 CEFs, ETFs and Future Returns

In additional tests, we examine whether embedded belief-crossing helps forecast future CEF and ETF returns. Prior research generally assumes that the average investor belief is closer to the fundamental value than the beliefs of the most optimistic investors (e.g., Diether, Malloy and Scherbina, 2002). If short-sale constraints are binding, stocks with higher investor disagreement therefore tend to be overpriced and experience lower future returns. Since belief-crossing reduces investor disagreement, CEFs and ETFs with high embedded belief-crossing should bring not only lower prices but also higher future returns compared with CEFs and ETFs that have low embedded belief-crossing.

As shown in Online Appendix Table A2, we observe exactly that. We estimate pooled OLS regressions of one-year returns of CEFs and ETFs on the same set of independent variables as in the CEF- and ETF-discount regressions. We include year-fixed effects. *T*-statistics are based on standard errors clustered by year.

We find that CEFs and ETFs that have high embedded belief-crossing bring higher subsequent returns compared with CEFs and ETFs that have low embedded belief-crossing. In particular, a one-standard deviation increase in belief-crossing forecasts 0.83% higher CEF and ETF returns (t-statistic = 2.64) over the ensuing year.

4.2 CEFs and Investor Sentiment

One potential concern with our CEF analysis is that embedded belief-crossing may be positively related to investor sentiment, which, in turn, affects the CEF discount (Lee, Shleifer and Thaler, 1991). In robustness tests, we re-estimate our main regression equation, but we now include *The Conference Board Consumer Confidence Index* as a proxy for investor sentiment. We also include interaction terms between the Consumer Confidence Index and measures of costs of arbitrage: the portfolio-weighted average market capitalization, the portfolio-weighted average institutional ownership, and the portfolio-weighted average idiosyncratic volatility. Since investor sentiment exhibits only time-series variation, for these additional tests we no longer include year-quarter fixed effects. As presented in Online Appendix Table A3, we find that controlling for sentiment has little effect on the coefficient estimate for *InvCov*.

4.3 ETF Capital Flows

As noted above, ETFs have much smaller discounts compared with CEFs due to the presence of authorized participants, who can create and redeem large blocks of an ETF's underlying assets should the value of the underlying assets diverge too much from the value of the overall fund. To the extent that authorized participants exploit discrepancies between the value of a fund and that of the fund's underlying assets, *changes* in embedded belief-crossing should affect capital flows going into and out of ETFs. To illustrate, consider an increase in *InvCov*, which then leads to an increase in the fund discount. Authorized participants should buy ETF shares in the secondary market, redeem those shares, and sell the underlying portfolio to reap a sure profit. This mechanism translates to a flow *out of* the ETF. In other words, $\Delta InvCov$ should negatively affect ETF flows.

To test this prediction, we re-estimate the ETF premium regression, but replace the dependent variable with the average monthly percentage flow in the corresponding quarter.[15] We also first-difference our independent variables to reflect the fact that ETF flows respond to changes in, rather than the level of, embedded belief-crossing. We include year-quarter-fixed effects. We no longer include fund-fixed effects since all of our variables are now first-differenced. *T*-statistics are based on standard errors clustered by both fund and year-quarter.

The results are presented in Table 4. As shown in Column 1, the coefficient estimate for $\Delta InvCov$ is -0.380 (t-statistic = -3.05), suggesting that a one-standard-deviation increase in $\Delta InvCov$ leads to a 0.38% increase in monthly outflows. For reference, the average monthly ETF flow in our sample is 1.6%. When augmenting our measure of embedded belief-crossing with (1-*IO*), the coefficient estimate increases to -0.440 (t-statistic = -2.56). When augmenting our measure of embedded belief-crossing with (1-*IO*) * *SI*, the coefficient estimate becomes -0.405 (t-statistic = -2.70). These results indicate that authorized participants indeed redeem blocks of ETF shares in response to an ETF's trading at a discount due to changes in embedded belief-crossing.[16]

5. Additional Results

In our final analysis section, we examine whether our mechanism extends to the corporate sector, in particular M&As and conglomerates. To preview, while not as clean of a setting

[15] Flows to ETFs are defined as percentage changes in shares outstanding over two consecutive periods (e.g., Da and Shive, 2015).

[16] While the evidence in this subsection suggests that authorized participants help make markets more efficient by trading against discounts that arise from embedded belief-crossing effects, Online Appendix Table A4 provides an example where authorized participants—through their actions—sometimes destabilize prices.

as CEFs and ETFs, the results from this section are at the very least consistent with our framework and, when considered jointly with the CEF and ETF results, strongly suggest that embedded belief-crossing and short-sale constraints are important forces.

5.1 Mergers and Acquisitions

The combined announcement day return of an acquirer and a target can be seen as partly reflecting the difference between the value of the joint firm (i.e., "the portfolio value") and the sum of the values of the acquirer and target operating separately (i.e., "the sum of the individual component values"). If embedded belief-crossing lowers the value of the whole relative to the sum of its parts, embedded belief-crossing between an acquirer and a target should lower the combined announcement day return.

To test whether combined announcement day returns decrease with embedded belief-crossing, we estimate a pooled OLS regression with year fixed effects across the 405 M&A events that meet our data requirements. The dependent variable is the combined announcement day return (as a %). The independent variables include *InvCov* and controls as described in Section 3.3. *T*-statistics are based on standard errors clustered by year.

Consistent with our hypothesis, Table 5, Column 1, shows that the coefficient estimate for *InvCov* is -1.713 (*t*-statistic = -4.72). This estimate suggests that a one-standard-deviation increase in *InvCov* comes with a 1.713% lower combined announcement day return.

One concern with our interpretation of the M&A results is that M&As for which beliefs cross—i.e., M&As for which investor groups that like the acquirer (target) dislike the target (acquirer)—tend to create low synergies, hence, our combined announcement day return result.

To assess the validity of this concern, we conduct the following two tests. First, to the extent that synergies are reflected in subsequent operating performance and to the extent that belief-crossing is indeed negatively correlated with M&A synergies, M&As with higher belief-crossing should produce worse operating performance going forward. We experiment with a number of operating performance measures within a regression framework: ROA, return on equity (ROE), net profit margin, and sales growth. As shown in Online Appendix Table A5, our crossing variable does not associate with any of these operating performance measures in the five years after an M&A. (The results are nearly identical if we instead look at operating performance in the next 10 or 15 years.)

In our second test, we exploit variation in long-run stock returns. Again, if short-sale constraints are binding, a decrease in investor disagreement should reduce overpricing and thus generate relatively higher future returns. M&As with high belief-crossing—i.e., M&As with the largest reductions in investor disagreement—should therefore experience not only lower combined announcement day returns but also higher future returns compared with M&As that have low belief-crossing. The synergy story does not share this prediction.

Consistent with the belief-crossing interpretation, Online Appendix Table A6 shows that belief-crossing between an acquirer and a target strongly and positively forecasts post-M&A stock returns: a one-standard-deviation increase in belief-crossing predicts nearly 10% higher returns (t-statistic = 4.30) in the year following an M&A.

5.2 Conglomerates

Our final analysis considers conglomerate firms. Following prior studies (e.g., Lang and Stulz, 1994), we estimate both a pooled OLS regression with year fixed effects and a Fama-MacBeth (1973) regression. The dependent variable is the conglomerate firm discount computed on an annual basis. The independent variable of primary interest is the sales-weighted average industry disagreement. Since brokerages do not issue forecasts for individual sectors, we are unable to compute *Crossing* and *InvCov* in this setting. The controls are as described in Section 3.4.

If embedded belief-crossing lowers the value of the whole relative to the sum of its parts, disagreement, which positively relates to embedded belief-crossing, should increase the diversification discount. Consistent with this prediction, Table 6 shows that the coefficient estimate for *Disagreement* is -0.043 (t-statistic = -2.92) in the pooled OLS setting; in the Fama-MacBeth setting, the estimate is -0.069 (t-statistic = -6.10). These estimates indicate that a one-standard-deviation increase in *Disagreement* is associated with a 4.3% to 6.9% increase in the conglomerate firm discount. Relative to the average conglomerate discount of 14.9% in our sample, these estimated increases are economically substantial.

6. Conclusion

Our paper makes the novel observation that investor beliefs frequently cross, which can cause the whole to trade at a discount relative to the sum of its parts. Utilizing four seemingly unrelated settings: CEFs, ETFs, M&As and conglomerates, we provide evidence supportive of our argument. We speculate that investor belief-crossing not only helps explain the pricing of CEFs, ETFs, M&As and conglomerates, but that the implications of our argument are much broader and pertinent to any situation that involves portfolios of companies or large companies operating in multiple segments.[17]

Our paper also contributes to the behavioral finance literature by providing relatively clean evidence for the relevance of disagreement models and short-sale constraints in explaining asset prices.

[17] For instance, our argument implies that, in the presence of strong belief-crossing, managers are better off "unbundling" their large portfolios into smaller, more sharply focused portfolios that have strong appeal among "niche investor groups." Such a conversion to smaller, more sharply focused portfolios would be somewhat akin to the shift in the cable industry from large cable packages (sometimes containing more than two hundred TV channels) to significantly smaller and more customized cable packages (Popper 2015).

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Table A1. Variable Description.

Variable	Description
Panel A: Closed-End Funds (CEFs)	
CEF Premium	A CEF's market price minus its NAV, divided by its NAV.
Disagreement	The portfolio-weighted average price-scaled earnings forecast dispersion of the top ten stocks held by a CEF.
Crossing	We compute the Spearman rank correlation between earnings forecasts for each top-ten stock pair. *Crossing* is the portfolio-weighted average of these correlations, multiplied by negative one.
InvCov	For each top-ten stock pair, we compute the Spearman rank correlation between earnings forecasts, multiplied by their respective forecast dispersions. *InvCov* is the portfolio-weighted average of these interactions, multiplied by negative one.
Inverse Price (Pos) [(Neg)]	The inverse of a CEF's lagged market price if the CEF trades at a premium [discount], and zero otherwise.
Dividend Yield (Pos) [(Neg)]	The sum of the dividends paid by a CEF over the past one year divided by the CEF's lagged market price if the CEF trades at a premium [discount], and zero otherwise.
Liquidity Ratio	A CEF's one-month turnover, divided by the portfolio-weighted average one-month turnover of the stocks held by the CEF. If the stock is listed on NASDAQ, we divide the number of shares traded by two.
Expense Ratio	A CEF's expense ratio.
Excess Idiosyncratic Volatility	The difference between the idiosyncratic volatility of a CEF and the portfolio-weighted average idiosyncratic volatility of the stocks held by the CEF. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-month return window using daily returns.
Excess Skewness	The difference between the return skewness of a CEF and the portfolio-weighted average return skewness of the stocks held by the CEF. Return skewness is calculated as $s = \frac{\frac{1}{22}\sum_{t=1}^{22}(r_t-\mu)^3}{\hat{\sigma}^3}$, where s is calculated using daily returns over a one-month return window, ˘ is the mean return, and $\hat{\sigma}^3$ is the cube of the return standard deviation.

Table A1. Continued.

Variable	Description
Panel B: Exchange-Traded Funds (ETFs)	
ETF Premium	An ETF’s market price minus its NAV, divided by its NAV.
Disagreement	The portfolio-weighted average price-scaled earnings forecast dispersion of the top ten stocks held by an ETF.
Crossing	We compute the Spearman rank correlation between earnings forecasts for each top-ten stock pair. *Crossing* is the portfolio-weighted average of these correlations, multiplied by negative one.
InvCov	For each top-ten stock pair, we compute the Spearman rank correlation between earnings forecasts, multiplied by their respective forecast dispersions. *InvCov* is the portfolio-weighted average of these interactions, multiplied by negative one.
Inverse Price (Pos) [(Neg)]	The inverse of a CEF’s lagged market price if the CEF trades at a premium [discount], and zero otherwise.
Dividend Yield (Pos) [(Neg)]	The sum of the dividends paid by a CEF over the past one year divided by the CEF’s lagged market price if the CEF trades at a premium [discount], and zero otherwise.
Liquidity Ratio	An ETF’s one-month turnover, divided by the portfolio-weighted average one-month turnover of the stocks held by the ETF. If a stock is listed on NASDAQ, we divide the number of shares traded by two.
Expense Ratio	An ETF’s expense ratio.
Excess Idiosyncratic Volatility	The difference between the idiosyncratic volatility of an ETF and the portfolio-weighted average idiosyncratic volatility of the stocks held by the ETF. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-month return window using daily returns.
Excess Skewness	The difference between the return skewness of an ETF and the portfolio-weighted average return skewness of the stocks held by the ETF. Return skewness is calculated as $s = \frac{\frac{1}{22}\sum_{t=1}^{22}(r_t-\mu)^3}{\hat{\sigma}^3}$, where s is calculated using daily returns over a one-month return window, ˇ is the mean return, and $\hat{\sigma}^3$ is the cube of the return standard deviation.

Table A1. Continued.

Variable	Description
Panel C: Mergers and Acquisitions	
Combined Announcement Day Return	The average cumulative abnormal return [-1,+1] across an acquirer and a target where t=0 is the day (or the ensuing trading day) of an M&A announcement, weighted by the acquirer's and target's market capitalization in the month prior to the announcement.
Acquirer (Target) Announcement Day Return	The cumulative abnormal return [-1,+1] for an acquirer (a target) where t=0 is the day (or the ensuing trading day) of an M&A announcement.
Disagreement	The average earnings forecast dispersion (scaled by price) across an acquirer and a target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement.
Crossing	The Spearman rank correlation between brokerage earnings forecasts issued for an acquirer and those issued for a target, multiplied by negative one.
InvCov	The Spearman rank correlation between brokerage earnings forecasts issued for an acquirer and those issued for a target, multiplied by the respective earnings forecast dispersions, multiplied by negative one.
Acquirer (Target) Market Capitalization	An acquirer's (a target's) market capitalization in the month prior to the announcement.
Acquirer (Target) Market-to-Book Ratio	An acquirer's (a target's) market-to-book ratio.
Acquirer (Target) ROA	An acquirer's (a target's) ratio of earnings before interest and tax to total assets.
Acquirer (Target) Leverage	An acquirer's (a target's) ratio of long-term debt to total assets.

Table A1. Continued.

Variable	Description
Acquirer (Target) Operating Cash Flow	An acquirer's (a target's) ratio of operating cash flows to total assets.
Acquirer (Target) ATP index	ATP index is an anti-takeover provision index based on six provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. The index runs from 0 through 6 based on the number of these provisions that a company adopts in a given year (Bebchuk, Cohen and Ferrel, 2009).
Tender Offer	Variable that equals one if a tender offer is made and zero otherwise.
Hostile Offer	Variable that equals one if a takeover is considered hostile and zero otherwise.
Competing Offer	Variable that equals one if there are multiple offers made by various companies and zero otherwise.
Cash Only	Variable that equals one if an acquirer uses cash only to purchase a target and zero otherwise.
Stock Only	Variable that equals one if an acquirer uses stocks only to purchase a target and zero otherwise.
Same Industry	Same industry is a dummy variable that equals one if acquirer and target companies are in the same two-digit SIC codes and zero otherwise.
Combined Idiosyncratic Volatility	The average idiosyncratic volatility across an acquirer and a target, weighted by the acquirer's and target's market capitalization in the month prior to an announcement. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-month return window using daily returns.
Combined Skewness	The average return skewness across an acquirer and a target, weighted by the acquirer's and target's market capitalization in the month prior to an announcement. Return skewness is calculated as $s = \frac{\frac{1}{12}\sum_{t=1}^{12}(r_t-\mu)^3}{\hat{\sigma}^2}$, where s is calculated using monthly returns over a one-year return window, μ is the mean return, and σ̂3 is the cube of the return standard deviation.

Table A1. Continued.

Variable	Description
Panel D: Conglomerates	
Diversification Premium	The difference between a conglomerate's market-to-book ratio (*MB*) and its imputed *MB*, divided by the conglomerate's imputed *MB*. For each two-digit-SIC code industry in which the conglomerate operates, we calculate the average *MB* across all single-segment firms that are in the same size tercile as the conglomerate. The imputed *MB* is the sales-weighted average of those industry *MBs*.
Disagreement	For each two-digit SIC code in which a conglomerate operates, we calculate the average price-scaled earnings forecast dispersion across all single-segment firms that are in the same size tercile as the conglomerate. *Disagreement* is the sales-weighted average of those industry dispersions.
Total Assets	A conglomerate's total assets.
Leverage	The ratio of long-term debt to total assets.
Profitability	The ratio of earnings before interest and tax to net revenue.
Investment Ratio	The ratio of capital expenditures to net revenue.
Excess Idiosyncratic Volatility	The difference between the idiosyncratic volatility of a conglomerate and its imputed idiosyncratic volatility. Idiosyncratic volatility is estimated based on residuals from the Fama-French Three-Factor model over a one-year return window using monthly returns. For each two-digit SIC-code industry in which a conglomerate operates, we compute the average idiosyncratic volatility across all single-segment firms that are in the same size tercile as the conglomerate. The imputed idiosyncratic volatility is the sales-weighted average of those industry volatilities.
Excess Skewness	The difference between the return skewness of a conglomerate and its imputed return skewness. Return skewness is calculated as $s = \frac{\frac{1}{12}\sum_{t=1}^{12}(r_t-\mu)^3}{\hat{\sigma}^3}$, where s is calculated using monthly returns over a one-year return window, μ is the mean return, and $\hat{\sigma}^3$ is the cube of the return standard deviation. For each two-digit SIC-code industry in which the conglomerate operates, we compute the average skewness across all single-segment firms that are in the same size tercile as the conglomerate. The imputed return skewness is the sales-weighted average industry skewness.

Table 1. Descriptive Statistics

This table presents descriptive statistics for our samples of closed-end funds (CEFs), exchange-traded funds (ETFs), mergers and acquisitions (M&As), and conglomerates. Panel A reports descriptive statistics for the pooled sample of CEF observations. Panel B reports descriptive statistics for the pooled sample of ETF observations. Panel C reports descriptive statistics for the pooled sample of M&A observations. Panel D reports descriptive statistics for the pooled sample of conglomerate observations. All variables are described in Appendix A1.

	N	Mean	Std Dev	25th	Median	75th
Panel A: Closed-End Funds						
CEF Premium	1,906	-0.043	0.150	-0.124	-0.090	-0.020
*InvCov (*100)*	1,906	-0.003	0.056	-0.006	-0.001	0.003
Disagreement	1,906	0.001	0.002	0.001	0.001	0.001
Crossing	1,906	-0.018	0.145	-0.075	-0.014	0.041
Inverse Price	1,906	0.097	0.070	0.056	0.076	0.110
Dividend Yield	1,906	0.067	0.046	0.037	0.074	0.095
Liquidity Ratio	1,906	3.422	3.283	1.724	2.543	4.038
Expense Ratio	1,906	1.216	0.544	0.970	1.140	1.380
Excess Idiosyncratic Volatility	1,906	-0.003	0.006	-0.006	-0.004	-0.001
Excess Skewness	1,906	-0.135	0.604	-0.480	-0.109	0.227
Panel B: Exchange-Traded Funds						
ETF Premium (bps)	4,310	-0.471	36.147	-8.028	-1.957	7.995
*InvCov (*100)*	4,310	-0.010	0.049	-0.011	-0.003	0.020
Disagreement	4,310	0.002	0.004	0.001	0.001	0.002
Crossing	4,310	-0.044	0.137	-0.103	-0.037	0.019
Inverse Price	4,310	0.033	0.022	0.017	0.027	0.043
Dividend Yield	4,310	0.016	0.015	0.007	0.013	0.019
Liquidity Ratio	4,310	1.076	2.382	0.263	0.654	1.216
Expense Ratio	4,310	0.005	0.002	0.004	0.005	0.006
Excess Idiosyncratic Volatility	4,310	-0.005	0.005	-0.006	-0.004	-0.003
Excess Skewness	4,310	-0.070	0.427	-0.313	-0.071	0.164

Table 1. Continued.

	N	Mean	Std Dev	25th	Median	75th
Panel C: Mergers and Acquisitions						
Combined Announcement Day Return	405	0.021	0.070	-0.016	0.011	0.055
Acquirer Announcement Day Return	405	-0.013	0.070	-0.049	-0.010	0.017
Target Announcement Day Return	405	0.227	0.260	0.093	0.187	0.312
*InvCov (*100)*	405	0.002	0.255	-0.030	0.000	0.025
Disagreement	405	0.002	0.004	0.000	0.001	0.002
Crossing	405	-0.019	0.605	-0.500	0.000	0.462
Acquirer Characteristics:						
Acquirer Market Capitalization	405	27,740	48,391	1,838	6,223	25,489
Acquirer Market-to-Book Ratio	405	3.498	3.257	1.624	2.366	4.155
Acquirer ROA	405	0.094	0.084	0.041	0.090	0.145
Acquirer Leverage	405	0.563	0.217	0.416	0.565	0.717
Acquirer Operating Cash Flow	405	0.105	0.078	0.059	0.107	0.153
Acquirer ATP Index	405	2.208	1.121	1.889	2.000	3.000
Target Characteristics:						
Target Market Capitalization	405	2,623	5,105	4,029	9,896	22,340
Target Market-to-Book Ratio	405	3.984	2.849	1.489	2.233	3.403
Target ROA	405	0.052	0.131	0.015	0.064	0.115
Target Leverage	405	0.523	0.251	0.298	0.537	0.724
Target Operating Cash Flow	405	0.073	0.115	0.027	0.080	0.135
Target ATP Index	405	2.077	1.308	1.581	2.000	2.272
Panel D: Conglomerates						
Diversification Premium	14,792	-0.149	0.750	-0.577	-0.175	0.244
Disagreement	14,792	0.008	0.025	0.001	0.002	0.005
Number of Segments	14,792	2.358	0.658	2.000	2.000	3.000
Total Assets	14,792	5,809	31,853	93.9	450.6	2,402.1
Leverage	14,792	0.193	0.162	0.050	0.172	0.295
Profitability	14,792	0.051	0.192	0.028	0.075	0.127
Investment Ratio	14,792	0.072	0.108	0.022	0.039	0.073
Excess Idiosyncratic Volatility	14,792	-0.005	0.066	-0.037	-0.014	0.013
Excess Skewness	14,792	-0.012	0.646	-0.427	-0.031	0.379

Table 2. Embedded Belief Crossing and Closed-End Fund Discounts

This table reports coefficient estimates from pooled OLS regressions of quarterly CEF premia on a measure of investor disagreement and belief crossing across the CEF's holdings. The dependent variable is the difference between the CEF's market price and the CEF's NAV, divided by the CEF's NAV [%]. We construct *InvCov* as follows: For each stock pair involving securities of the CEF's top-ten holdings, we compile a list of brokerage houses that cover both firms and we compute the Spearman rank correlation in earnings forecasts between these two firms; we also compute the forecast dispersion for each of the two firms. *PairwiseCov* is the product of the Spearman rank correlation and the average forecast dispersion. We aggregate *PairwiseCov* to *InvCov* as the portfolio-weighted average *PairwiseCov* across all stock pairs, multiplied by negative one. A large positive realization of *InvCov* suggests a high level of embedded belief crossing. In Columns 2 and 3, we augment *InvCov* with (1-*IO*) and with (1-*IO*) * *SI*, respectively, where *IO* is the residual institutional ownership and *SI* is short interest. We describe how we construct the remaining variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include fund- and year-quarter-fixed effects. *T*-statistics are reported in parentheses and are based on standard errors clustered by both fund and year-quarter. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Baseline *InvCov* (1)	Embed *IO* into *InvCov* (2)	Embed *IO* and *SI* into *InvCov* (3)
InvCov	-0.491***	-0.567***	-0.499**
	(-2.68)	(-2.61)	(-2.48)
Disagreement	0.388	0.569	0.478
	(0.91)	(1.26)	(1.14)
Crossing	0.034	0.085	0.010
	(0.19)	(0.49)	(0.05)
IO		0.675	0.711
		(1.35)	(1.38)
SI			-0.769
			(-1.48)
Inverse Price$_{pos}$	-1.017	-0.955	-0.933
	(-0.59)	(-0.55)	(-0.54)
Inverse Price$_{neg}$	-4.712***	-4.669***	-4.722***
	(-2.61)	(-2.60)	(-2.63)
Dividend Yield$_{pos}$	1.554	1.517	1.519
	(1.54)	(1.50)	(1.50)
Dividend Yield$_{neg}$	-0.130	-0.125	-0.045
	(-0.26)	(-0.25)	(-0.09)
Liquidity Ratio	1.372***	1.286**	1.400***
	(2.70)	(2.55)	(2.75)
Expense Ratio	0.925	0.884	0.945
	(1.07)	(1.06)	(1.11)
Excess Idiosyncratic Volatility	0.526	0.504	0.426
	(0.75)	(0.71)	(0.61)
Excess Skewness	0.135	0.145	0.140
	(1.23)	(1.31)	(1.36)
# Obs.	1,906	1,906	1,906
Adj. R^2	0.843	0.844	0.844

Table 3. Embedded Belief Crossing and Exchange-Traded Fund Discounts

This table reports coefficient estimates from pooled OLS regressions of quarterly ETF premia on a measure of investor disagreement and belief crossing across the ETF's holdings. The dependent variable is the difference between the ETF's market price and the ETF's NAV, divided by the ETF's NAV [%]. We construct *InvCov* as follows: For each stock pair involving securities of the ETF's top-ten holdings, we compile a list of brokerage houses that cover both firms and we compute the Spearman rank correlation in earnings forecasts between these two firms; we also compute the forecast dispersion for each of the two firms. *PairwiseCov* is the product of the Spearman rank correlation and the average forecast dispersion. We aggregate *PairwiseCov* to *InvCov* as the portfolio-weighted average *PairwiseCov* across all stock pairs, multiplied by negative one. A large positive realization of *InvCov* suggests a high level of embedded belief crossing. In Columns 2 and 3, we augment *InvCov* with (1-*IO*) and with (1-*IO*) * *SI*, respectively, where *IO* is the residual institutional ownership and *SI* is short interest. We describe how we construct the remaining variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include fund- and year-quarter-fixed effects. *T*-statistics are reported in parentheses and are based on standard errors clustered by both fund and year-quarter. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Baseline *InvCov* (1)	Embed *IO* into *InvCov* (2)	Embed *IO* and *SI* into *InvCov* (3)
InvCov	-1.465**	-1.697**	-1.744**
	(-2.24)	(-2.41)	(-2.54)
Disagreement	0.582	0.586	-0.259
	(0.47)	(0.58)	(-0.42)
Crossing	0.505	0.576	0.520
	(1.04)	(1.24)	(1.09)
IO		-0.249	-0.163
		(-0.19)	(-0.13)
SI			2.800**
			(1.98)
Inverse Price$_{pos}$	3.683	3.758	3.816
	(0.83)	(0.86)	(0.90)
Inverse Price$_{neg}$	-10.344**	-10.274**	-10.211**
	(-2.02)	(-2.03)	(-2.08)
Dividend Yield$_{pos}$	1.822	1.822	1.742
	(1.30)	(1.30)	(1.26)
Dividend Yield$_{neg}$	-4.561***	-4.538***	-4.624***
	(-3.22)	(-3.21)	(-3.32)
Liquidity Ratio	-1.896	-1.874	-2.117
	(-1.12)	(-1.11)	(-1.29)
Expense Ratio	2.357	2.363	2.142
	(0.64)	(0.64)	(0.57)
Excess Idiosyncratic Volatility	-1.875	-1.903	-1.719
	(-0.71)	(-0.72)	(-0.66)
Excess Skewness	0.583	0.597	0.597
	(0.64)	(0.65)	(0.66)
# Obs.	4,310	4,310	4,310
Adj. R^2	0.372	0.372	0.373

Table 4. Embedded Belief Crossing and Exchange-Traded Fund Flows

This table reports coefficient estimates from pooled OLS regressions of monthly ETF flows on a measure of investor disagreement and belief crossing. The dependent variable is the percentage change in the number of shares outstanding of the ETF. The independent variables are as in Table 3, but now represent quarterly changes (rather than levels). All independent variables are normalized to have a standard deviation of one. We include year-quarter-fixed effects (we no longer include fund-fixed effects since all of our variables are now first-differenced). *T*-statistics are reported in parentheses and are based on standard errors clustered by both fund and year-quarter. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Baseline *InvCov* (1)	Embed *IO* into *InvCov* (2)	Embed *IO* and *SI* into *InvCov* (3)
Δ*InvCov*	-0.380***	-0.440**	-0.405***
	(-3.05)	(-2.56)	(-2.70)
Δ*Disagreement*	-0.434**	-0.426**	0.068
	(-2.48)	(-2.36)	(0.83)
Δ*Crossing*	0.165	0.153	0.393**
	(1.40)	(1.30)	(2.35)
Δ*IO*		-0.133	-0.098
		(-0.08)	(-0.58)
Δ*SI*			0.134
			(0.76)
Δ*Dividend Yield*	0.437*	0.445*	0.447*
	(1.75)	(1.76)	(1.75)
Δ*Liquidity Ratio*	-1.277***	-1.278***	-1.279***
	(-8.54)	(-8.50)	(-8.51)
Δ*Expense Ratio*	-0.024	-0.035	-0.038
	(-0.30)	(-0.44)	(-0.49)
Δ*Excess Idiosyncratic Volatility*	-0.517***	-0.502***	-0.444***
	(-4.71)	(-4.68)	(-3.83)
Δ*Excess Skewness*	0.057	0.059	0.049
	(0.32)	(0.33)	(0.27)
Lagged Returns	Yes	Yes	Yes
Lagged Flows	Yes	Yes	Yes
# Obs.	8,092	8,092	8,092
Adj. R^2	0.026	0.025	0.025

Table 5. Embedded Belief Crossing and Combined M&A Announcement Day Returns

This table reports coefficient estimates from regressions of combined M&A announcement day returns on a measure of investor disagreement and belief crossing about the acquirer and the target. The dependent variable is the average cumulative abnormal return [-1,+1] across the acquirer and the target where t=0 is the day (or the ensuing trading day) of the M&A announcement, weighted by the acquirer's and the target's market capitalization in the month prior to the announcement [%].We construct *InvCov* as follows: We compile a list of brokerage houses that cover both the acquirer and the target and we compute the Spearman rank correlation in earnings forecasts between these two firms; we also compute the forecast dispersion for each of the two firms. *InvCov* is the product of the Spearman rank correlation and the average forecast dispersion, multiplied by negative one. A large positive realization of *InvCov* suggests a high level of embedded belief crossing. In Panels B and C, we augment *InvCov* with (1-*IO*) and with (1-*IO*) * *SI*, respectively, where *IO* is the residual institutional ownership and *SI* is short interest. We describe how we construct the remaining variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include year-fixed effects. *T*-statistics are reported in parentheses and are based on standard errors clustered by year. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Baseline *InvCov* (1)	Embed *IO* into *InvCov* (2)	Embed *IO* and *SI* into *InvCov* (3)
InvCov	-1.713***	-1.380***	-1.057***
	(-4.72)	(-3.44)	(-2.71)
Disagreement	-0.763**	-0.373	-0.428
	(-2.11)	(-0.99)	(-1.06)
Crossing	0.215	0.276	-0.026
	(0.61)	(0.72)	(-0.07)
IO		-0.408	-0.520
		(-0.91)	(-1.16)
SI			0.385
			(0.86)
Acquirer Characteristics:			
ln(Acquirer Market Cap)	-1.382	-1.134	-0.962
	(-1.42)	(-1.09)	(-0.89)
Acquirer Market-to-Book Ratio	0.618	0.590	0.570
	(1.51)	(1.41)	(1.36)
Acquirer ROA	0.321	0.334	0.383
	(0.60)	(0.61)	(0.69)
Acquirer Leverage	-0.081	0.006	-0.064
	(-0.16)	(0.01)	(-0.12)
Acquirer Operating Cash Flow	-0.723	-0.521	-0.550
	(-1.22)	(-0.96)	(-1.00)
Acquirer ATP Index	-0.131	-0.148	-0.116
	(-0.27)	(-0.30)	(-0.23)

Table 5. Continued.

	Baseline *InvCov* (1)	Embed *IO* into *InvCov* (2)	Embed *IO* and *SI* into *InvCov* (3)
Target Characteristics:			
ln(Target Market Cap)	0.050	0.108	0.061
	(0.06)	(0.13)	(0.07)
Target Market-to-Book Ratio	-0.416	-0.430	-0.454
	(-1.12)	(-1.13)	(-1.19)
Target ROA	1.284**	1.462**	1.437**
	(2.13)	(2.39)	(2.34)
Target Leverage	0.322	0.334	0.377
	(0.70)	(0.72)	(0.81)
Target Operating Cash Flow	-1.333**	-1.515***	-1.529***
	(-2.37)	(-2.66)	(-2.67)
Target ATP Index	0.780	0.667	0.697
	(0.79)	(0.67)	(0.69)
Deal Characteristics:			
Relative Size	-1.596**	-1.470*	-1.394*
	(-2.12)	(-1.92)	(-1.82)
Combined Idiosyncratic Volatility	0.415	0.351	0.349
	(0.78)	(0.64)	(0.63)
Combined Skewness	-0.123	-0.095	-0.119
	(-0.35)	(-0.26)	(-0.33)
Tender Offer	-0.650	-0.727	-0.662
	(-0.61)	(-0.67)	(-0.61)
Hostile Offer	2.249	2.434	2.414
	(0.73)	(0.77)	(0.76)
Competing Offers	1.650	1.721	1.908
	(0.83)	(0.85)	(0.94)
Cash Only	2.964***	2.784***	2.763***
	(3.41)	(3.14)	(3.08)
Stock Only	-0.551	-0.616	-0.776
	(-0.62)	(-0.68)	(-0.85)
Same Industry	0.600	0.721	0.756
	(0.81)	(0.95)	(0.99)
# Obs.	405	405	405
Adj. R^2	0.314	0.294	0.288

Table 6. Investor Disagreement and Conglomerates

This table reports coefficient estimates from regressions of annual diversification premia on a measure of disagreement about the conglomerate's underlying segments. The dependent variable is the difference between the conglomerate's market-to-book ratio (*MB*) and its imputed *MB*, divided by the conglomerate's imputed *MB* [%]. Imputed *MB* and *Disagreement* are the sales-weighted average two-digit-SIC*MB* and the sales-weighted average two-digit-SIC price-scaled earnings forecast dispersion across the conglomerate's segments as of *t*. We use information in June of calendar year *t* to compute the market value of equity and we use accounting data from the fiscal year ending in the previous calendar year *t*-1 to compute the book value of equity. Earnings forecasts are for annual earnings with fiscal year ending in calendar year *t*-1. We describe how we construct the remaining variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. In Column (1), we estimate a pooled OLS regression with year-fixed effects; *t*-statistics are computed using standard errors clustered by both firm and year. In Column (2), we estimate annual Fama-MacBeth (1973) regressions; *t*-statistics are based on Newey-West (1987) standard errors with one lag and are reported in parentheses. The Adj. R^2 in Column (2) is the average Adj. R^2 of the cross-sectional regressions. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1)	(2)
Disagreement	-0.043***	-0.069***
	(-2.92)	(-6.10)
Number of Segments	-0.014	-0.015***
	(-1.08)	(-2.90)
ln(TotalAssets)	-0.719***	-0.849***
	(-9.20)	(-16.98)
ln(TotalAssets)^2	0.621***	0.732***
	(7.79)	(15.92)
Leverage	0.072***	0.800***
	(4.69)	(7.14)
Profitability	0.015	0.026***
	(1.11)	(3.37)
Investment Ratio	0.024*	0.031***
	(1.89)	(3.42)
Excess Idiosyncratic Volatility	0.059***	0.048***
	(3.64)	(3.61)
Excess Skewness	0.021***	0.019***
	(3.19)	(2.86)
# Obs.	14,792	31
Adj. R^2	0.075	0.086