Offsetting Disagreement and Security Prices[*]

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Abstract

We propose that investors in financial markets are generally less excited about portfolios than they are about individual companies because companies liked by some investors are often not liked by other investors. This makes it impossible to construct portfolios that contain (only) every investor's favorite companies. The level of excitement that a portfolio of companies receives, therefore, is less than the sum of the level of excitement that the individual companies receive from their most fervent supporters. In the presence of binding short-sale constraints, wherein prices are set by the most optimistic investors, this difference in the level of excitement becomes priced and the value of the portfolio is lower than the sum of the values of the individual components. Utilizing mergers and acquisitions, closed-end funds, exchange-traded funds, and conglomerates in which the value of the aggregate portfolio and the values of the underlying components can be separately evaluated, we present evidence supporting our proposition.

JEL Classification: G11, G12, G14, G20

Keywords: Investor Disagreement, Belief Crossing, Portfolio Discounts

1. Introduction

We propose that in financial markets the whole is generally valued at *less* than the sum of its parts because companies liked by some investors are not necessarily liked by other investors. This makes it impossible to construct a portfolio that contains only every investor's favorite companies. The level of excitement that a portfolio of companies generates among optimists is, therefore, generally lower than the combined level of excitement that the individual companies in the portfolio generate among their most fervent supporters. In the presence of binding short-sale constraints, this discrepancy in the 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 believes that Apple and Microsoft are worth $5 and $10, respectively. 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. However, if Apple and Microsoft were combined and traded "as a package," either because Apple and Microsoft decided to merge or because a publicly traded investment company, such as a closed-end fund, held shares of both companies, no investor would be willing to pay more than $15 for Apple and Microsoft combined because, while both Apple and Microsoft have their own sets of investors who hold them in high regard, 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 offsetting disagreement channel we propose draws on an interaction effect between disagreement and belief-crossing (hereafter referred to as *embedded 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. In addition, if the same investor holds the most optimistic belief across all assets, even if there is a high level of disagreement, there will be no discrepancy between the whole and the sum of its parts, as both the value of the overall portfolio and the value of each component are determined by the same investor.

The first setting we exploit to empirically assess the validity of our mechanism is that of mergers and acquisitions (M&As). The M&A setting provides the closest parallels to our simple example. The key variable of interest is the combined announcement day return of an acquirer and a target, which reflects, among other things, 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"). Based on our argument, the combined M&A announcement day return should decrease as embedded belief-crossing between the acquirer and the target increases.

Motivated by prior studies, we approximate investor beliefs via quarterly earnings forecasts issued by brokerage firms. Because most investors work with a small number of brokers to execute trades and gather information, investors rely more heavily on information provided by some brokerage firms than others. Disagreements over a given stock across brokerages, as well as belief-crossing for a pair of stocks, therefore provide useful information about the level of disagreement and belief-crossing that is present among investors.

To proceed, we gather quarterly earnings forecasts issued by brokerages covering both acquirers and targets. We compute the average dispersion in earnings forecasts across any given acquirer and target prior to an M&A announcement and we augment it with information about whether the brokerage with the most optimistic earnings forecasts for the acquirer tends to issue the most pessimistic earnings forecasts for the target. The resulting variable, *InvCov* (Inverse Covariance), is such that large positive realizations imply high levels of embedded belief-crossing. Based on our mechanism, our regression of combined announcement day returns on *InvCov* and various control variables should produce a strong negative slope on *InvCov*. Consistent with this prediction, our estimate for *InvCov* is -1.713 (*t*-statistic = -4.72), which suggests 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.

One potential concern with our interpretation is that the decision to merge might be endogenous, driven by a number of hard-to-measure factors such as perceived synergies between acquirers and targets. If belief-crossing and perceived synergies are negatively correlated—i.e., M&As with higher belief-crossing create lower value—this could potentially explain the observed negative relationship between belief-crossing and combined announcement day returns. We believe this alternative explanation is unlikely to be the driving force of our results. To the extent that perceived synergies are reflected in subsequent operating performance, we should expect M&As with higher belief-crossing to generate worse operating performance going forward. In sharp contrast, we find that M&As with high belief-crossing subsequently perform better than M&As with low belief-crossing.

Another prediction of our framework is that if acquirer and target firm managers are aware of the negative effect of belief-crossing on the valuation of the combined firm, we should see fewer M&As between firm pairs with higher investor belief-crossing. Consistent with this prediction, results from additional analyses suggest that when the level of embedded belief-crossing is "too high," firm managers are more likely to abandon plans to merge. In particular, we compute *InvCov* for actual acquirer–target pairs and pseudo acquirer–target pairs, which are similar to the actual acquirer–target pairs by reference to a host of firm characteristics. In logit regressions, we find that a one-standard-deviation increase in *InvCov* reduces the likelihood that an M&A is announced by 32.6% (relative to the unconditional likelihood).

Our mechanism also helps explain the behavior of US equity closed-end funds (CEFs), US equity exchange-traded funds (ETFs), and conglomerates.[1] CEFs are corporations holding portfolios of stocks. Both CEFs and their holdings are traded on stock exchanges. Based on our

[1] 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.

proposed channel, we should expect a fund's market value to fall below the sum of the values of the fund's underlying assets and we should expect this discount to increase with the level of embedded belief-crossing.

We again approximate investor disagreement and belief-crossing via brokerage-level earnings forecasts. 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 top-ten holdings. We do so because we conjecture that when investors gauge their level of excitement about a portfolio, they focus on the portfolio's top-ten holdings, which are readily observable on the fund's website, the fund's factsheet, and financial information aggregators such as Morningstar, the Closed-End-Fund Center, or Yahoo! Finance. As we discuss in Section 3.5, the focus on the top ten also helps reduce the dimensionality of the data and bring the calculation to a manageable level. Having said that, our results are robust to including stocks outside of a fund's top ten.

Consistent with our prediction, we find that greater embedded belief-crossing among a fund's top holdings 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 (*t*-statistic = -2.68), which suggests 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%.

We make analogous observations for ETFs. ETFs are investment companies holding portfolios of securities, whereby both an ETF and its 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 used for CEFs, we find that ETF discounts increase with the level of embedded belief-crossing. 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.

Our mechanism also yields predictions regarding capital flows in and out of ETFs. An increase in embedded belief-crossing in a fund's underlying holdings 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 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%.

Our CEF and ETF results indicate that high embedded belief-crossing among a portfolio's holdings lowers the amount investors are willing to pay for such a portfolio. When initiating a CEF or an ETF, managers aware of this negative belief-crossing effect should therefore construct portfolios with relatively low embedded belief-crossing to minimize the discount and to maximize the proceeds from the initial public offering (IPO). Managers who find it difficult to construct such portfolios may forego IPOs altogether.

Our results support these predictions. We compute *InvCov* for both actual top-ten pairs and pseudo top-ten pairs, the latter of which are similar to the actual top-ten pairs by reference to a host of firm characteristics, but which end up being excluded from the fund's top-ten holdings. We find that increasing *InvCov* by one standard deviation reduces the likelihood that a pair is included in the fund's top-ten holdings by 31.6% (relative to the unconditional probability). In addition, we find that high values of average embedded belief-crossing among stocks in an industry sector substantially reduce the likelihood that an IPO of a CEF or ETF specializing in that sector will be issued.

Our final test considers conglomerate firms. Conglomerates are corporations operating in multiple industry segments. To the extent that investor excitement differs by industry, the valuation ratios of conglomerates should fall below the valuation ratios of firms operating in a single industry; this wedge should increase with the level of disagreement about the conglomerates' underlying industry segments.[2] Approximating investor disagreement using brokerage earnings forecasts, we find evidence that the "diversification discount" indeed increases with disagreement about conglomerates' underlying industry segments.

The remainder of the paper is organized as follows: Section 2 places our study in the literature. Section 3 describes the data and our main variables of interest. Section 4 presents our findings, and Section 5 concludes.

2. Background and Contribution

Our study is closely related to a class of behavioral models referred to as "disagreement models." 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. 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 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

[2] Because the individual segments of a conglomerate are not traded separately and need to be approximated by standalone firms from the same industries, we are unable to construct a measure of belief-crossing.

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.[3]

In this paper we distinguish the disagreement model from alternative interpretations tied to growth options and investor optimism by deriving an implication that is unique to the disagreement/short-sale constraint framework. In particular, we note that a company liked by investor A may not be liked by investor B. Similarly, a company liked by investor B may not be liked by investor A. In other words, in financial markets investor beliefs frequently cross. Since investor beliefs cross, it is impossible to construct a portfolio that perfectly pleases large groups of investors and contains only every investor's favorite companies (as one investor's favorite company may not be another investor's favorite company). 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

[3] 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.

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.

In addition to shedding light on the applicability of a prominent behavioral framework and the relevance of a much-debated source of market friction—that of short-sale constraints—we contribute to the literature by making the more general point that investor beliefs sometimes cross. Our evidence suggests that this relatively "innocent" point can help explain the behavior 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.

3. Data and Variables

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

3.1 Mergers and Acquisitions

Our 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 remaining variables in Appendix Table A1. For ease of interpretation, 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 built 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:

$$CAR(-1,1) = w_A * CAR(-1,1)_A + w_T * CAR(-1,1)_T, \tag{1}$$

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%.

3.2 Closed-End Funds

Our second analysis focuses on US equity closed-end funds. CEFs are publicly traded companies. Rather than using the proceeds from an 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 the fund against the market value of the CEF's underlying holdings.

We include in our sample CEFs 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 remaining variables 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.

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.[4]

Quarterly CEF premia are calculated as follows:

$$Premium_{i,t} = \frac{Price_{i,t} - NAV_{i,t}}{NAV_{i,t}}. \quad (2)$$

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 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).

3.3 Exchange-Traded Funds

ETFs are similar to CEFs in that both a fund and the fund'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. 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.

[4] 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).

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

3.4 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 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 remaining variables 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 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 M&As, CEFs, ETFs, 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. [5] 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)

An example of stock coverage by analysts and brokerage firms

Given that most investors deal with a small number of brokers for trade execution and information gathering, 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 the brokerage level provides

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

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

Note that we need take no 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 the 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.[6]

3.5.1 Disagreement and Crossing – M&As

In the case of M&As, the construction of our embedded belief-crossing variable is relatively straightforward. We first compute the price-scaled earnings forecast dispersion for both an acquirer and a target:

$$Dispersion_j = \frac{StDev\left(Forecast(EPS)_{h,j}\right)}{P_j}, \tag{4}$$

where $Forecast(EPS)_{h,j}$ is brokerage h's most recent forecast for quarterly earnings-per-share of firm j. Because each brokerage firm assigns only one of its analysts to cover stock j, brokerage

[6] 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 underlying assets and investors pricing overall portfolios. Our results are virtually unchanged.

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 earnings announcement date and the earnings announcement date to fall within the ninety-day period prior to an M&A announcement 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 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:

$$Disagreement = w_A Dispersion_A + w_T Dispersion_T. \quad (5)$$

In the next step, we compile a 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 between the acquirer and the target, multiplied by negative one:

$$Crossing = Corr\big(Forecast(EPS_A), Forecast(EPS_T)\big) * (-1). \quad (6)$$

When the most optimistic investor in the acquirer is also the most optimistic investor in the target ("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 acquirer is the most pessimistic investor in the target ("belief-crossing"), the correlation gravitates towards negative one and the *Crossing* variable gravitates towards positive one. That is, a high realization for *Crossing* implies a high level of investor 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, *InvCov* (Inverse Covariance), which, as we mentioned in the introduction, we refer to as embedded belief-crossing:

$$InvCov = Disagreement * Crossing. \quad (7)$$

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

3.5.2 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) and we first compute the pairwise embedded belief-crossing for each stock pair *j*,*l* covered by at least two common brokerage houses:

$$InvCov(j,l) = Disagreement_{j,l} * Crossing_{j,l}. \tag{8}$$

Disagreement is the portfolio weighted-average dispersion across stocks *j* and *l* and *Crossing* is the Spearman rank correlation in earnings forecasts between stocks *j* and *l*, multiplied by negative one.

We then aggregate pairwise *InvCov* to the portfolio level, defined as the portfolio-weighted average *InvCov* across all 45 stock pairs (*j*, *l*):

$$InvCov = \frac{\sum_{j,l}(w_j+w_l)*InvCov(j,l)}{\sum_{j,l}(w_j+w_l)} \tag{9}$$

As before, a large positive realization of *InvCov* implies a high level of embedded belief-crossing. Note that the portfolio average *InvCov* in equation (9) 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.

The number of possible stock pairs increases exponentially with the 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 an 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 the fund's factsheet.[7] 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 of holdings.[8]

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 99th 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 construct our crossing variable for conglomerates.

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

4.1 Mergers and Acquisitions

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

[8] 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.

To test the prediction that the combined announcement day return decreases 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 3.1. As shown in Table 2, Column 1, the coefficient estimate for *InvCov* is -1.713 (*t*-statistic = -4.72), which suggests that a one-standard-deviation increase in *InvCov* comes with a 1.713% lower combined announcement day return.

Our framework also predicts that the offsetting disagreement effect should strengthen with the degree to which both an acquirer and a target 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*.[9] 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).[10] Large positive realizations of these variables indicate 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. Column 2 reports results when we embed (1–*IO*) into *InvCov*; Column 3 reports results when we embed (1–*IO*) * *SI* into *InvCov*. Both variables strongly negatively associate with combined announcement day returns.

[9] Specifically, we multiply *Dispersion* in equation (4) by (1-*IO*) for each stock; we then follow the same procedure described in equations (5) through (9) to define *InvCov* with embedded (1-*IO*).

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

4.1.1 Synergies

One potential concern with our interpretation of the M&A results is that the decision to merge is endogenous, driven by a number of hard-to-measure factors, the most important of which is perceived synergies. If investor belief-crossing is negatively correlated with perceived synergies, i.e., if M&As with higher belief-crossing create less value, our documented combined announcement day return result may simply be an artifact of low perceived synergies.

To address 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 perceived 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 A2, 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. 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 experience lower future returns. By extension, a decrease in investor disagreement reduces overpricing and thus generates 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 A3 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. In other words, in the data, higher belief-crossing (and, presumably, smaller synergies) come with higher future stock returns.

While neither test can fully rule out the possibility that our results are driven partially by perceived synergies, both tests provide additional evidence that belief-crossing is responsible for a meaningful portion of the documented announcement-day-return pattern.

4.1.2 Supply-Side Considerations

To the extent that firm managers recognize the negative valuation effect of embedded belief-crossing, the likelihood that an M&A between a firm pair occurs should *decrease* with the level of embedded belief-crossing. We conduct the following experiment to test this idea: For each M&A announcement in our sample, we construct a set of counterfactual firm pairs, which are similar to the actual M&A pair along an array of observable firm characteristics (e.g., firm size, book-to-market ratio, and past one-year return), but involve firms that did not engage in M&As. Specifically, for each firm involved in an M&A, we identify ten pseudo-acquirers and ten pseudo-targets that are the closest to the actual acquirer and target based on the propensity-score-matching approach.

In our first regression specification, we individually match the actual acquirer with each of the ten pseudo-targets (i.e., fix the actual acquirer), resulting in ten counterfactual firm pairs. In our second regression specification, we reverse the matching and individually match the actual target with each of the ten pseudo-acquirers (i.e., fix the actual target), resulting in ten counterfactual firm pairs. In our third regression specification, we match each of the ten pseudo-acquirers with each of the ten pseudo-targets (i.e., allow both the acquirer and target to be substituted), and select the ten pairs that are the closest to the actual acquirer–target pair.

We then estimate a logit regression, wherein the dependent variable equals one for actual M&A pairs and zero for counterfactual firm pairs. The independent variables are the same as in the combined announcement-day-return regression, but are now averaged to the firm-pair level. As shown in Table 3, we find that, across all three regression specifications, high embedded belief-crossing indeed reduces the probability of observing an actual M&A. For example, our third regression specification reported in Column 3 produces a coefficient estimate for *InvCov* of -0.132 (*t*-statistic = -4.13). This estimate suggests that a one-standard-deviation increase in embedded belief-crossing reduces the likelihood of observing an M&A by nearly 3%, representing a 32.6% drop relative to the unconditional likelihood of observing an M&A.

4.1.3 Carve-Outs

The "reverse" of an M&A is a carve-out. Our mechanism therefore predicts not only fewer M&As when embedded belief-crossing is high but also more carve-outs. One challenge when testing how embedded belief-crossing relates to carve-out decisions is that we cannot construct an ex-ante measure of embedded belief-crossing: by construction, we observe analyst forecasts of subsidiaries only after the carve-out takes place. As a result, we can use only an ex-post measure of embedded belief-crossing to explain managers' decisions to split firms. A second, related challenge is that we do not observe the degree of belief-crossing between the two subsidiaries for firms that choose not to split.

To deal with these issues, we focus on carve-outs in which the two components (the spun-off segment and the remaining firm) are in the same two-digit SIC-code industry. We then compute the average belief-crossing across all firm-pairs in each industry/year-quarter and examine whether industry-level embedded belief-crossing predicts a greater chance of observing carve-outs in that industry.

We estimate a pooled logit regression, in which the observations are at the industry/year-quarter level. The dependent variable equals one if the industry/year-quarter has at least one carve-out and zero otherwise. The independent variables include embedded belief-crossing, market capitalization, book-to-market ratio, and past one-year returns, all at the industry/year-quarter level. As presented in Online Appendix Table A4, we find that high belief-crossing indeed comes with more carve-outs. The coefficient estimate in Column 1 of 0.099 (*t*-statistic = 2.15) implies that a one-standard-deviation increase in belief-crossing increases the likelihood of observing at least one carve-out by 2.3%, representing a 28.05% increase relative to the unconditional likelihood.

4.2 Closed-End Funds and Exchange-Traded Funds

We next extend our analysis to 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 quarterly CEF premium (%) or the quarterly ETF premium (bps). The independent variables include *InvCov* and the controls described in Section 3.2.

Table 4 presents the results for CEFs. As shown in Column 1, 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%. The results become even 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).

Our ETF results are similar to those for CEFs. As reported in Column 1 of Table 5, 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. When augmenting our measure of embedded belief-crossing with (1-*IO*), the coefficient estimate increases to -1.697 (*t*-statistic = -2.41). When augmenting our measure of embedded belief-crossing with (1-*IO*) * *SI*, the coefficient estimate increases further, to -1.744 (*t*-statistic = -2.54).

In additional tests, we also examine whether embedded belief-crossing helps forecast future CEF and ETF returns on shares. Our prediction is that, 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 A5 and, resembling what we find for M&As, CEFs and ETFs with high embedded belief-crossing indeed bring higher subsequent returns compared with CEFs and ETFs with low embedded belief-crossing. A one-standard deviation increase in belief-crossing forecasts 0.83% higher CEF and ETF returns (*t*-statistic = 2.64) over the ensuing year.

4.2.1 CEFs and Investor Sentiment

One potential concern with our CEF analysis is that embedded belief-crossing might somehow be positively related to investor sentiment, which, in turn, would affect the CEF discount (Lee, Shleifer and Thaler, 1991). In additional 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 the costs of arbitrage for underlying portfolios: 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 A6, we find that controlling for sentiment has little effect on the coefficient estimate for *InvCov*.[11]

4.2.2 ETF Capital Flows

As we have noted, 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

[11] A related concern is that fund managers may choose to initiate new funds in response to investor sentiment and that this may partially account for our finding that CEF discounts increase with investor belief-crossing. To alleviate this concern, we exclude the first two years following a fund's inception (investor sentiment exhibits significant time variation and it is unlikely that managers can predict investor sentiment a few years down the road). As presented in Online Appendix Table A7, our results are largely unchanged under this modification—a one standard-deviation change in belief crossing is now associated with a 0.48% (*t*-statistic = 2.10) increase in the CEF discount.

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, Δ*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.[12] We also first-difference our independent variables; for example, the independent variable of primary interest now is the quarterly *change* in *InvCov*.

The results are presented in Table 6. As shown in Column 1, the coefficient estimate for Δ*InvCov* is -0.380 (*t*-statistic = -3.05), suggesting that a one-standard-deviation increase in Δ*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.[13]

4.2.3 Supply-Side Considerations

To the extent that fund managers are aware of the negative effect of investor belief-crossing on portfolio value, managers initiating a CEF or an ETF should construct portfolios with relatively low embedded belief-crossing to maximize the proceeds from the IPO. Further, should managers find it difficult to construct such portfolios, they may forego IPOs altogether.

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

[13] 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 A8 provides an example where authorized participants—through their actions—appear to destabilize prices.

Our first test draws on the M&A pseudo-firm analysis. For each top-ten stock in a fund's portfolio, we identify ten pseudo-top-ten stocks that did not make it to the top-ten list, but are very similar to the top-ten stock in question by reference to a host of firm characteristics (e.g., firm size, book-to-market ratio, and past one-year returns). More specifically, for each top-ten stock we identify ten non-top-ten stocks that are the closest to the stock in question using a propensity-score-matching approach. Each CEF or ETF in each year-quarter *t* then produces 45 actual top-ten stock pairs (=n*(n-1)/2) and 4,500 pseudo pairs.

We estimate a pooled logit regression in which the dependent variable equals one for the actual top-ten pairs and zero for the counterfactual pairs. Our independent variables include the level of embedded belief-crossing of the relevant stock pair, the average market capitalization of the relevant stock pair, the average book-to-market ratio, and the average past one-year stock returns.

Based on our argument, actual top-ten pairs should involve lower belief-crossing than pairs of stocks that fund managers did not choose as part of their top-ten holdings. As shown in Table 7, our results support this prediction. Column 1 shows that the coefficient estimate for *InvCov* is -0.109 (*t*-statistic = -3.52). This estimate implies that a one-standard-deviation increase in belief-crossing reduces the likelihood that a stock will be included in a fund's top-ten holdings by 0.5%, representing a 31.6% drop relative to the unconditional likelihood. The results become stronger when embedding our proxies for short-sale constraints into *InvCov* (Columns 2 and 3).

Our second test draws on the carve-out setting. Specifically, we compute, for each two-digit SIC-code industry in each year-quarter, the average level of embedded belief-crossing across all stock pairs within that industry. We then examine whether the creation of CEFs and ETFs specializing in that industry is tied to the corresponding level of belief-crossing. As with our carve-out regression, the observations are at the industry/year-quarter level. We estimate a pooled logit regression in which the dependent variable equals one if the industry/year-quarter has at least one CEF or ETF IPO specializing in that industry and zero otherwise. The independent variables include embedded belief-crossing, market capitalization, book-to-market ratio, and past one-year returns, all at the industry/year-quarter level.

As shown in Table 8, our evidence reveals that higher industry-average belief-crossing indeed forecasts fewer CEF/ETF IPOs. Specifically, our estimate for *InvCov* is -0.146 (*t*-statistic = -2.18). This implies that a one-standard-deviation increase in industry-average belief-crossing reduces the likelihood of having at least one CEF/ETF initiation by 3.3%, representing a 31.1% drop relative to the unconditional likelihood.

4.3 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 the *Crossing* and *InvCov* measures in this setting.

As shown in Table 9, 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.

As we did in the M&A setting, in additional analyses we also examine how investor belief-crossing relates to conglomerates' decisions to enter or exit industry segments. Consistent with our M&A results, Online Appendix Table A9 shows that higher disagreement in an industry segment reduces the fraction of conglomerates entering that segment and increases the fraction of conglomerates exiting that segment.

5. Conclusion

This paper builds on the notion that, even if investors disagree strongly about the value of the individual components of a portfolio of stocks, as long as their relative views are not perfectly and positively correlated across these components disagreement partially offsets at the aggregate portfolio level. In the presence of binding short-sale constraints, this can lead a portfolio to trade at a discount relative to the sum of its components. This discount should increase with both the level of investor disagreement and the degree to which their relative views cross.

Our paper contributes to the literature by providing relatively clean evidence for the practical relevance of investor disagreement and short-sale constraints in determining asset prices. Moreover, our paper provides a novel, unifying explanation for a number of seemingly unrelated asset-pricing phenomena: observed substantial variation in M&A announcement day returns, CEF and ETF discounts, and the diversification discount, which prior studies have tied to distinct mechanisms. In general, the implications of our argument that investor beliefs cross should be relevant to any situation that involves portfolios of companies and large companies operating in multiple segments.

Our papers also has managerial implications. In particular, our argument implies that, in the presence of very strong belief-crossing, managers are better off “unbundling” their large portfolios and conglomerates into smaller portfolios and more sharply focused companies that have strong appeal among “niche investor groups.” Such a conversion to smaller, more sharply focused portfolios and companies would be somewhat akin to the shift the cable industry is already experiencing with its conversion 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: 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 $\hat{\sigma}$3 is the cube of the return standard deviation.

Table A1. Continued.

Variable	Description
Panel B: 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	The inverse of a CEF's market price.
Dividend Yield	The sum of the dividends paid by a CEF over the past one year, divided by the CEF's market price.
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, μ is the mean return, and $\hat{\sigma}^3$ is the cube of the return standard deviation.

Table A1. Continued.

Variable	Description
Panel C: 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	The inverse of an ETF's market price.
Dividend Yield	The sum of the dividends paid by an ETF over the past one year divided by the ETF's market price.
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, μ is the mean return, and $\hat{\sigma}^3$ 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 mergers and acquisitions (M&As), closed-end funds (CEFs), exchange-traded funds (ETFs), and conglomerates. Panel A reports descriptive statistics for the pooled sample of M&A observations. Panel B reports descriptive statistics for the pooled sample of CEF observations. Panel C reports descriptive statistics for the pooled sample of ETF 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: 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

Table 1. Continued.

	N	Mean	Std Dev	25th	Median	75th
Panel B: 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 C: 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
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 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 2. 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 3. Likelihood of Mergers and Acquisitions

This table reports coefficient estimates from logit regressions of M&A announcements on a measure of investor disagreement and belief crossing about actual acquirer-target pairs and pseudo acquirer-target pairs. For each M&A announcement in our sample, we construct a set of counterfactual firm pairs, which are similar to the actual M&A pair along an array of observable firm characteristics, but involve firms that did not engage in an M&A. Specifically, for each firm involved in an M&A, we identify ten pseudo acquirers and ten pseudo targets that are in the same two-digit-SIC-code industry as, and are the closest to, the actual acquirer and the actual target along the dimensions of firm size, book-to-market ratio and past one year returns, using a propensity score matching approach. In Column (1), we individually match the actual acquirer with each of the ten pseudo targets, resulting in ten counterfactual firm pairs. In Column (2), we reverse the matching and individually match the actual target with each of the ten pseudo acquirers, resulting in ten counterfactual firm pairs. In Column (3), we match each of the ten pseudo acquirers with each of the ten pseudo targets, resulting, again, in ten counterfactual firm pairs. The dependent variable equals one for actual M&A pairs, and zero for counterfactual firm pairs. *InvCov* is the level of embedded belief crossing of the actual- and the pseudo acquirer-target pairs. The remaining independent variables are the same as in the combined-announcement day-return regression, but are now averaged to the firm-pair level. All independent variables are normalized to have a standard deviation of one. We include year-fixed effects. *Z*-values 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.

	Pseudo Target Only (1)	Pseudo Acquirer Only (2)	Pseudo Acquirer and Pseudo Target (3)
InvCov	-0.090***	-0.134***	-0.132***
	(-2.73)	(-3.94)	(-4.13)
Disagreement	0.069	-0.081	-0.084
	(0.91)	(-1.11)	(-1.11)
Crossing	0.261**	0.419***	0.323***
	(2.46)	(3.92)	(3.20)
Acquirer Characteristics:	Yes	Yes	Yes
Target Characteristics:	Yes	Yes	Yes
Deal Characteristics:	Yes	Yes	Yes
# Obs.	3,091	3,630	3,740
Pseudo R^2	0.038	0.019	0.023

Table 4. 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 5. 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 6. 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 5, 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 7. Embedded Belief Crossing and Top-Ten Holdings at Inception

This table reports coefficient estimates from logit regressions of CEF and ETF holdings around the time of the CEF/ETF inception on a measure of investor disagreement and belief crossing across actual- and potential top-ten holdings. For each top-ten stock in the fund's portfolio (as of the first available holdings-data date), we identify ten pseudo-top-ten stocks that did not make it to the top-ten list, but are very similar to the top-ten stock in question by reference to a host of firm characteristics. Specifically, for each top-ten stock, we identify ten non-top-ten stocks that are in the same two-digit-SIC-code industry as, and are the closest to, the actual top-ten stock, along the dimensions of firm size, book-to-market ratio and past one year returns, using a propensity score matching approach. Our dependent variable equals one for the actual top-ten pairs, and zero for the counterfactual pairs. Our independent variables include the level of embedded belief crossing of the relevant stock pair (*InvCov*), the average market capitalization of the stock pair, the average book-to-market ratio of the stock pair and the average past one-year stock returns of the stock pair. 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. All independent variables are normalized to have a standard deviation of one. We include year-quarter-fixed effects. *Z*-values are reported in parentheses and are based on standard errors clustered by 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	-0.109***	-0.124***	-0.112***
	(-2.61)	(-2.80)	(-2.59)
Disagreement	-0.108	-0.158	-0.208
	(-0.96)	(-1.35)	(-1.28)
Crossing	0.208*	0.254**	0.219*
	(1.83)	(2.08)	(1.90)
Stock Characteristics:	Yes	Yes	Yes
# Obs.	53,335	53,335	53,335
Pseudo R^2	0.008	0.026	0.028

Table 8. Embedded Belief Crossing and Likelihood of Sector Fund Inceptions

This table reports coefficient estimates from logit regressions of sector-CEF IPOs and sector-ETF IPOs on a measure of investor disagreement and belief crossing about the sector. Specifically, we compute, for each two-digit SIC-code industry in each year-quarter, the average level of embedded belief crossing across all stock pairs within that industry. We then examine whether the creation of CEFs and ETFs specializing in that industry is tied to the corresponding level of belief crossing. The dependent variable equals one if the industry/year-quarter has at least one CEF or ETF IPO specializing in that industry, and zero otherwise. The independent variables include embedded belief crossing (*InvCov*), market capitalization, book-to-market ratio and past one-year returns, all at the industry/year-quarter level. 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. All independent variables are normalized to have a standard deviation of one. We include industry-fixed effects. *Z*-values are reported in parentheses and are based on standard errors clustered by 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	-0.146***	-0.176***	-0.135**
	(-2.80)	(-3.28)	(-2.23)
Disagreement	0.145	0.211	0.053
	(1.11)	(1.39)	(0.41)
Crossing	0.191	0.265	0.109
	(1.14)	(1.48)	(0.66)
IO		-0.478***	-0.424***
		(-2.81)	(-3.30)
SI			-0.720
			(-1.38)
Ln(Market Cap)	-0.284	-0.684	-0.808
	(-0.55)	(-1.34)	(-1.59)
BM	-0.442*	-0.504**	-0.529***
	(-1.85)	(-2.59)	(-3.02)
Momentum	0.404***	0.444***	0.412***
	(2.73)	(3.17)	(2.91)
# Obs.	816	816	816
Pseudo R^2	0.049	0.057	0.049

Table 9. 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