OFFSETTING DISAGREEMENT AND SECURITY PRICES

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We propose that investor beliefs frequently "cross" in the sense that an investor may like company A, but dislike company B, while another investor may like company B, but dislike company A. Belief-crossing makes it almost impossible to construct a portfolio that is comprised solely of every investor's most favorite companies. This causes the level of excitement for portfolios to be generally less than the levels of excitement that individual companies receive from their most fervent supporters. Coupled with short-sale constraints, wherein prices are set by the most optimistic investors, this causes portfolios to trade at discounts. Utilizing various settings where the value of the portfolio and the values of the underlying components can be separately evaluated (e.g., closed-end funds), we present evidence supporting our proposition that, in financial markets, the "whole" is often less than the "sum of its parts."

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1. Introduction

A large body of work emphasizes that financial market participants often disagree about the fundamental value of a company and that, coupled with short-sale constraints, this has important asset pricing implications (Miller 1977; Diether, Malloy and Scherbina 2002; Duffie, Gârleanu, and Pedersen 2002; Chen, Hong and Stein 2002; Scheinkman and Xiong 2003; Hong and Stein 2007). In this study, we propose that financial markets are marked not only by investor disagreement, but also by variation in belief crossing: Sometimes, an investor may like companies A and B while a second investor may dislike companies A and B ("no belief crossing"). Other times, an investor may like company A but dislike company B while a second investor may like company B but dislike company A ("belief crossing"). We suggest and provide evidence that variation in belief crossing has important asset pricing ramifications.

Conceptually, we note that in the presence of belief crossing, it is almost impossible to construct a portfolio that is comprised solely of every investor's most favorite companies and in that regard perfectly pleases large investor groups. 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 a 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 portfolios trade at a discount relative to their underlying assets. The stronger the level of belief crossing is among investors, the more negatively investors perceive the "whole" relative to the "sum of its parts."

To illustrate, consider a simple setting of two investors and two firms, Apple and Microsoft. Investors disagree and their beliefs cross: The first investor is enthusiastic about Apple (perceived value = \$10), but not excited about Microsoft (perceived value = \$5). The second investor is enthusiastic about Microsoft (perceived value =\$10), but not excited about Apple (perceived value = \$5). While Apple and Microsoft each generate excitement among at least a subgroup of investors, because of belief crossing, no investor group is excited about the whole, "Apple-soft." In the presence of binding short-sale constraints, market prices reflect the valuations of the most bullish investors. The market values of Apple and Microsoft are thus \$10 each, while the market value for Apple-soft is \$15. The whole (here, \$15) thus trades at a significant discount relative to the sum of its parts (here, \$20).

The difference in how much investors value the whole relative to the sum of its parts widens with the interaction between disagreement and belief-crossing, hereafter referred to as *embedded belief-crossing*: Even if investor beliefs cross, as long as investors hold similar views about the value of each asset, the fact that investor beliefs cross is of little practical consequence. For instance, even if two investors value Apple at \$7.55 and \$7.45, while valuing Microsoft at \$7.45 and \$7.55, respectively, Apple and Microsoft will trade at \$7.55 each, the sum of each is \$15.10, whereas Apple-soft will trade at \$15. By the same token, even if there is investor disagreement at the firm level, as long as investor beliefs do *not cross* and a first investor group is excited about both Apple and Microsoft (while a second investor group dislikes both Apple and Microsoft) there will be a marginal investor, here, the first investor group, who values the whole just as highly as the sum of its parts.[1]

We use US equity closed-end funds (CEFs) as our main setting to empirically assess the validity of our argument that investor beliefs frequently cross and that in the presence of belief crossing the whole is valued at less than the sum of its parts. CEFs and their holdings both trade 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.

We impose two assumptions in our empirical design: First, we assume that investor beliefs can be approximated via quarterly earnings forecasts issued by brokerage firms. In particular, 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.

Second, in our paper, we are comparing how investors value "the whole" relative to "the sum of its parts." Since closed-end funds are mostly held by retail investors, we

[1] In the Online Appendix, we formalize our intuition within a stylized model. In particular, our model highlights the key prediction that short-sale constraints coupled with embedded belief crossing leads to a discount at the portfolio level.

believe that when a typical closed-end fund investor values "the whole," such an investor is more likely to look at a fund's top ten holdings than the full schedule of investments: Unlike the full holdings, top ten holdings are prominently displayed on a fund's website and a fund's fact sheet. They are also easily retrievable through fund information aggregators, such as Morningstar or the Wall Street Journal. In contrast, obtaining the full holdings requires going over a fund's annual report. Consistent with our conjecture, in a survey sent to 114 retail investors, 93%-100% of investors report to have considered sources, which prominently display a fund's top-ten holdings. 38%-44% of investors report to have considered the annual report.

To construct our measure of embedded belief crossing, for each of the 45 possible top ten stock pairs, we compute the average dispersion in earnings forecasts 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*.

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

To gauge whether it is embedded belief-crossing per se that generates our patterns, we examine whether our effect is stronger in situations in which a portfolio's underlying stocks are more short-sale constrained. We use two proxies for short-sale constraints: a) the interaction of retail ownership and short interest (e.g., Asquith, Pathak, and Ritter 2005) and b) daily lending fees (a direct measure of the cost of short selling). We find evidence strongly consistent with our proposition as a high level of embedded belief-crossing only lowers the value of the CEF relative to the value of its underlying assets when the assets are likely short-sale constrained.

In a second attempt to provide evidence that it is embedded belief-crossing per se that generates our patterns, we use broker mergers and closures (following Hong and Kacperczyk 2010; and Kelly and Ljungqvist 2012) as a negative shock to the level of embedded belief-crossing. Broker mergers and closures, hereafter simply referred to as broker closures, result in a drop of analyst coverage, which in turn decreases the level of embedded belief crossing.[2] Broker closures are unlikely to be informative about the future prospects of the affected stocks. We therefore believe that brokerage closures produce plausibly exogenous variation in the level of embedded belief crossing. Consistent with our main analysis and in line with a causal link, we find that when a CEF experiences a decrease in its level of embedded belief crossing tied to a broker closure, its price (relative to its NAV) rises strongly and disproportionately compared with CEFs whose holdings are not affected by a broker closure.

In subsequent analyses, we provide evidence that embedded belief-crossing is a broad and general force that helps explain a range of patterns across a wide set of securities and events, including exchange-traded funds (ETFs), mergers and acquisitions (M&As), and conglomerates.

Just like CEFs, 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. 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.

[2] A drop in belief crossing is mechanical if analyst coverage drops to one: in such case, within our empirical framework, all investors condition on the same information and there is neither disagreement nor belief crossing. In the data, we observe a strong decrease in the level of embedded belief crossing even in cases analyst coverage does not drop to one.

Regarding M&As, we note that 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]

Finally, 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 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 proposition that investor beliefs frequently cross, which, combined with short-sale constraints, can cause a whole to be valued at less than the sum of its parts. Our evidence suggests that variation in belief crossing helps explain a wide range of price patterns and that, at least in financial markets, the whole is commonly valued at less than the sum of its parts. In general, our framework should be applicable to any situation involving portfolios of companies or large companies operating in multiple segments.

In addition to introducing a new construct, we also shed light on the applicability of a prominent behavioral framework—that of disagreement models—and the relevance

[3] Duffie, Gârleanu 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 3.2.3, we are unable to construct a measure of embedded belief-crossing for conglomerates.

of a much-debated 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, Gârleanu, 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 the optimists only, prices are generally upward biased. Moreover, prices rise as 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 suggests 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, in turn, can lead to higher current valuation and lower future returns. In addition, a growing body of work argues that few stocks are meaningfully short-sale constrained and that the practical relevance of short-sale constraints should be questioned altogether (e.g., Asquith, Pathak and Ritter 2005; Boehmer, Jones and Zhang 2008; Kaplan, Moskowitz and Sensoy 2013).

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 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 the 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. In our stylized model with belief-crossing and short selling constraint (see Online Appendix: A Model of Investor Disagreement and Belief Crossing), we show explicitly how offsetting disagreement can lead to portfolio discounts.

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 a relatively low level of investor disagreement, whereas the underlying components tend to exhibit relatively high levels of 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.

The idea that investor disagreement "has implications not only for the prices of particular securities, but also for the valuation of firms formed by mergers, of conglomerates, and of closed end investment companies" goes back to at least Miller (1977). Two contemporaneous working papers, Bhandari (2016) and Reed, Saffi and Van Wesep (2016) empirically assess Miller's proposition and examine how investor disagreement affects corporate spinoffs and conglomerates assuming that beliefs perfectly cross. In contrast, we emphasize that the level of belief crossing varies significantly across stock pairs and we show conceptually (now with the help of a stylized model) that this has important asset pricing implications. Our empirical analysis corroborates the view that variation in belief crossing helps explain asset prices. We further emphasize variation in belief crossing as a broad and general force that helps explain a wide set of patterns across a spectrum of securities, ranging from closed-end funds to exchange-traded funds, to M&As, to conglomerates.

3. Data and Variables

In this section, we introduce our CEF setting (Section 3.1.1), our ETF setting (Section 3.1.2), our M&A setting (Section 3.1.3) and our conglomerates setting (Section 3.1.4). We discuss our embedded belief-crossing variable in Section 3.2.

3.1 Sample and Measure of the Whole-relative-to-the-Sum-of-its-Parts

3.1.1 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 ("the whole") against the market value of its underlying holdings ("the sum of its parts").

We identify CEFs via share codes 14 and 44 in the CRSP database. We obtain CEF price-per-share and net asset value-per-share (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 Morningstar.[5]

Our measure of "the Whole-relative-to-the-Sum-of-its-Parts" is the quarterly CEF premium, calculated as:

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

While price and NAV data are available at a higher frequency, we measure the CEF premium 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 3.2, can be computed only on a quarterly basis. As shown in Table 1, the average CEF premium in our sample is -4.3% (or the average CEF "discount" is 4.3%), with a standard deviation of 15.0%. These figures are similar to those reported in prior studies (e.g.,

[5] 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).

Bodurtha, Kim, and Lee 1995; Klibanoff, Lamont, and Wizman 1998; Chan, Jain, and Xia 2008; Hwang 2011).

3.1.2 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 all US equity exchange-traded funds except for ETFs that track broad market indices (e.g., S&P 500, Russell 1000, Russell 2000, Wilshire 4500, Wilshire 5000)[6] 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.

Our measure of "the Whole-relative-to-the-Sum-of-its-Parts" for ETFs is again constructed using equation (1). 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 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.

3.1.3 Mergers and Acquisitions

Our data sources for our sample of 405 M&As are SDC, CRSP, and COMPUSTAT. Our sample period runs from 1989 through 2014. 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"). For

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

M&As, our measure of "the Whole-relative-to-the-Sum-of-its-Parts" thus 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:

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

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%.

3.1.4 Conglomerate Firms

Conglomerates are firms operating in multiple industry segments. Our data sources are CRSP and COMPUSTAT. Our final sample spans the period 1984–2014 and contains 2,792 conglomerates.

The measure of "the whole relative to the sum of its parts" for conglomerates is the well-known diversification discount, which 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 1^{st} and 99^{th} 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, Polk and Saaá-Requejo 2001; Mitton and Vorkink 2010).

3.2 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 a 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 try to alleviate both concerns by computing our measures at the *brokerage* level.[7] 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 will also be more optimistic than investors paying more attention to Goldman Sachs' research. If so, disagreement and belief-crossing measured at 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

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

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 need not investors holding the underlying assets to be identical to the investors holding the 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. This does not seem implausible to us as analyst reports are disseminated to a wide range of audiences (through Yahoo Finance, Bloomberg, and other channels).[8]

3.2.1 Disagreement and Crossing – CEFs and ETFs

Our main analysis pertaining to CEFs and ETFs is based on CEFs'/ETFs' quarterly top-ten holdings. As alluded to in the introduction, we conjecture that retail investors, who are the primary investors in CEFs, are more likely to decide how much a given portfolio appeals to them based on a fund's top ten holdings than based on a fund's full holdings.

In particular, perhaps the nine most prominent information sources from which fund investors can draw when making their investment decision are: (1) a fund s website, (2) some other investment related website, such as Morningstar or a broker's website, (3) a fund's Fact Sheet, (4) a fund s Prospectus, (5) a fund s annual report, (6) discussion of a fund in a print or online article, (7) recommendation by a family member, friend, colleague, or other acquaintance, (8) recommendation by your financial advisor, or (9) advertisement.

Sources (1) through (3) prominently display a fund's top ten holdings (Online Appendix Figure A1). Only source (5), i.e., only a fund's annual report, displays a fund's full holdings (among many other things). We suspect that, comparatively speaking, few retail investors study a fund's annual report before making their investment decisions.

[8] Having said that, in additional tests, we re-estimate our primary regression equations separately for the subsamples in which CEFs' underlying assets are held more or less by retail investors, i.e., when there is more or less overlap between investors pricing the underlying assets and investors pricing the overall portfolios (CEFs are primarily held by retail investors). Our results remain significant in both subsamples, but are substantially stronger for the subsample of CEFs that are held primarily by retail investors.

Even if investors study a fund's annual report, the full schedule of investments is generally less prominently displayed than a fund's top ten holdings in sources (1) through (3).

To assess the validity of our suspicion, we design a Qualtrics survey as shown in Online Appendix Figure A1, in which we ask the following two questions: (1) "*If you ever invested in a fund and the fund was NOT an index fund, which sources of information did you use when first deciding which fund to invest in? [click all that apply]*," and (2) "*Once invested in a fund, which sources of information did you use when monitoring your investment and deciding whether to remain invested in the fund, pull your money out of the fund, or add more money to the fund? [click all that apply]*" As potential sources, we list the aforementioned nine sources, plus a tenth named "Others."

We recruit survey participants via Prolific (https://prolific.ac). We require that participants reside in the U.S. and report "yes" to the following two questions within Prolific: (1) "*Have you ever made investments (either personal or through your employment) in the common stock or shares of a company?*", (2) "*Have you invested in any of the following types of investment in the past?: ETF or ETC, Government Bonds or Stock Market.*" Within our Qualtrics survey, we also ask "*Have you ever invested in either a mutual fund, an exchange-traded fund, or a closed-end fund, and the fund was NOT just mimicking a broader index such as the S&P 500 (i.e., the fund was NOT an index fund)*," and we require survey participants to respond with "yes." Each participant is paid the equivalent of $30/hour for successful survey completion, which is above the minimum pay requested by Prolific of $7.50/hour. A total of 114 participants completed our survey.

We report our survey results in Online Appendix Figure A2. In short, for our two questions, we find that 93% or 100% of survey participants report to draw from sources (1), (2) or (3), all of which prominently display a fund's top-ten holdings. 38% or 44% of survey participants report to draw from the annual report, which, among many other things, contain a fund's full holdings (a typical annual report is around 40 pages long). Not all 93% or 100% of survey participants may strongly consider a fund's top-ten holdings when relying on sources (1) through (3). But relatively speaking, we still think it is more likely that fund investors value the whole based on a fund's top-ten holdings than based on a fund's full holdings. Under our conjecture, considering non-top ten holdings adds noise. Since top ten holdings on average account for "only" 29.2% of a typical closed-end fund portfolio, such noise can be substantial.[9]

Given our focus on top ten holding, each CEF/ETF in each year-quarter *t* produces 45 possible top-ten stock pairs (=n*(n-1)/2). For each top-ten stock pair *j,l* covered by at least two common brokerage houses, we first compute the price-scaled earnings forecast dispersion for both stock *j* and stock *l*:

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

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 99th percentile.

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

$$Disagreement = w_j Dispersion_j + w_l Dispersion_l. \tag{5}$$

In our 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:

$$Crossing = Corr\left(Forecast(EPS_j), Forecast(EPS_l)\right) * (-1). \tag{6}$$

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

[9] To assess the robustness of our findings, we also experiment with other portfolio cutoffs. Our results remain economically and statistically significant if we instead compute embedded belief-crossing based on the top 20, 30, 40, or 50 stocks (results available upon request).

("perfect belief-crossing") the correlation gravitates towards negative one and the *Crossing* variable gravitates towards positive one. A high realization of *Crossing* implies a high level of belief crossing.

Recall that our mechanism is a joint effect of *both* investor disagreement and investor belief-crossing. Our main independent variable thus 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.[10]

Our main variable, *InvCov*, exhibits some time-series persistence. For example, for the closed-end fund sample, the autocorrelation in *InvCov* is 37.6%. Almost all of the time-series variation in *InvCov* comes from changes in analyst forecasts as fund holdings are stable over time. More specifically, the correlation between *InvCov* and an alternative measure of *InvCov* using fund holdings in the previous quarter is 97.1%. For comparison, the correlation between *InvCov* and an alternative measure of *InvCov* using analyst forecasts from the previous quarter is 43.5%.

3.2.2 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

[10] Note that the portfolio average *InvCov* in equation (8) does not necessarily equal the product of the portfolio average *Disagreement* with 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, *Crossing*. Our main independent variable, *InvCov*, is the interaction of *Disagreement* with *Crossing*.

3.2.3 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.[11] 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.

4. Main Results

In the Online Appendix, we provide a stylized model to formalize our intuition that in the presence of belief crossing the whole is valued at less than the sum of its parts. The central prediction of the model is that short-sale constraints coupled with embedded belief crossing indeed leads to a discount in the portfolio value relative to the sum of its component values. In this section, we test this prediction for CEFs.

In particular, we estimate a pooled OLS regression on our CEF sample with either fund fixed effects or with both fund and year-quarter fixed effects. The dependent variable is the CEF *premium* (%) measured at a quarterly frequency. A negative coefficient thus indicates an *increase* in the CEF *discount*. The independent variables include *InvCov* and the following set of controls: *Inverse Price*, *Dividend Yield, Liquidity Ratio*, *Expense Ratio*, *Excess Idiosyncratic Volatility*, and *Excess Skewness*. We explain the construction of our control variables in Table A1. For ease of interpretation, all independent variables

[11] 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).

in our regression analysis are normalized to have a standard deviation of one. *T*-statistics are based on standard errors clustered by both fund and year-quarter.

Table 2 presents the results. Consistent with our prediction, the coefficient estimate for *InvCov* is -0.552 (*t*-statistic = -2.80) if we only include fund fixed effects or -0.491 (*t*-statistic = -2.69) if we include both fund and year-quarter fixed effects. These estimates imply that a one-standard-deviation increase in *InvCov* leads to a 0.49% to 0.55% increase in the CEF discount. These are sizable changes, as the average CEF discount in our sample is 4.3%.

For our control variables, we obtain a negative estimate for $InversePrice_{neg}$, which 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).

In our main regression specification, we do not control for investor sentiment, which is known to be associated with the average closed-end fund discount (e.g., Lee, Shleifer and Thaler 1991). This is because controlling for year-quarter fixed effects already accounts for market-wide investor sentiment. In robustness tests, we re-estimate our regression equation with fund fixed effects only, but also include either the Conference Board Consumer Confidence Index, the University of Michigan Consumer Sentiment Index (Lemmon and Portniaguina 2006) or the Baker-Wurgler sentiment index (Baker and Wurgler 2006). We also include interaction terms between the sentiment measure and measures of costs of arbitrage: the closed-end fund portfolio-weighted average market capitalization, the portfolio-weighted average institutional ownership, and the portfolio-weighted average idiosyncratic volatility. As presented in Online Appendix Table A1, controlling for sentiment has almost no effect on the coefficient estimate for *InvCov*.

4.1 The Role of Short-Sale Constraints

Our evidence to this point, while highly suggestive of embedded belief crossing having an effect on asset prices, is not free of alternative interpretations as one could argue that parts of our results suffer from omitted variable concerns.

Our first attempt to establish that it is truly embedded belief crossing per se that generates at least parts of our findings comes from examining whether our findings moderate with short-sale constraints. 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 interaction of short interest and one minus the fraction of shares held by institutions. Asquith, Pathak and Ritter (2005) suggest that stocks are short-sale constrained when demand to short stocks is high while the supply of lendable shares is low. Asquith et al. (2005) use short interest as a proxy for demand and one minus the fraction of shares held by institutions as a proxy for limited supply. Motivated by prior studies (e.g., Hong, Lim and Stein 2000), to ensure that institutional ownership does not effectively capture firm size, 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. We then interact short interest with one minus residual institutional ownership. Our second (perhaps cleaner) proxy for short-sale constraints is the average daily lending fee (from Markit) across the top ten stocks in a given fund/year-quarter. High lending fees are indicative of high short-sale costs and high short-sale constraints.

For each fund/year-quarter, we sort our top-ten stock pairs based on their average stock-pair level short-sale constraint. We then compute *InvCov* separately for the stock pairs that are in the top half based on their short-sale constraint, *High Constraint InvCov*, and for the stock pairs that are in the bottom half based on their short-sale constraint, *Low Constraint InvCov*. In our framework, embedded belief crossing should impact prices only if underlying assets are short-sale constrained. *High Constraint InvCov* should thus have much stronger explanatory power than *Low Constraint InvCov*.

Table 3 reports the results when replacing *InvCov* with *High Constraint InvCov* and *Low Constraint InvCov*. Consistent with our prediction, we find that for both our short-sale constraint proxies *High Constraint InvCov* strongly associates with CEF discounts while *Low Constraint InvCov* does not.

4.2 Broker Mergers and Closures

Our second attempt to establish that it is truly the mechanism of offsetting disagreement that generates at least parts of our findings is a difference-in-differences-type analysis around broker closures. Broker closures cause a drop in analyst coverage, which, in turn, generally lead to a sizeable drop in embedded belief crossing. In particular, we find that CEFs whose top-ten holdings are affected by a drop in analyst coverage due to a broker closure experience a drop in *InvCov* of 0.016 from the quarter prior to the broker closure to the quarter after such broker closure. To put this drop in perspective, the standard deviation of *InvCov* in our full CEF sample is 0.014.

In Table 4, we assess whether this plausibly exogenous drop in *InvCov* comes with a rise in the CEF premium. For each broker merger-closure in our sample period, we consider all CEFs in the two quarters surrounding the closure (Column (1)). In Column (2), we consider the surrounding four quarters. The observations here are thus at a broker closure/CEF/year-quarter level. We construct *AffectedGroup*, which equals one if a CEF's top-ten holdings are affected by a broker closure, and zero otherwise, and *Post*, which equals one after a broker closure, and zero otherwise. We then estimate a regression equation of CEF premium on *AffectedGroup*, *Post*, *AffectedGroup* * *Post* and the same set of controls as in our main regression equation. We include fund and broker merger/closure event fixed effects and we cluster our standard errors by both fund and broker merger/closure.

As reported in Table 4, across all columns, the estimate for *AffectedGroup* * *Post* is positive and significant. The estimate ranges from 0.519 (t-statistic = 1.86) to 0.643 (t-statistic = 2.28), suggesting that the drop in belief crossing around broker closures is accompanied by a rise in CEF prices relative to their NAVs of 52bps to 64bps.

4.3 Belief Crossing and Future Fund 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. Applied to our setting, since embedded belief-crossing reduces investor disagreement, CEFs with high embedded belief-crossing should bring not only lower prices but also higher future returns compared with funds that have low embedded belief-crossing.

In Column 1 of Online Appendix Table A2, we estimate pooled OLS regressions of CEF returns (four-factor adjusted) in the following year on the same set of independent variables as in the discount regressions, as well as time-fixed effects. We find that CEFs with high embedded belief-crossing indeed have higher subsequent returns compared with funds that have low embedded belief-crossing. In particular, a one-standard deviation increase in belief-crossing forecasts 43.8 bps higher four-factor fund alphas (t-statistic =1.81) over the ensuing year.

5. Other Settings and Additional Analyses

In our next set of analyses, we examine whether our mechanism extends to ETFs and the corporate sector, in particular M&As and conglomerates. To preview, while not as clean of a setting as CEFs, the results from this section are at the very least consistent with our framework and, when considered jointly with the CEF, suggest that embedded belief-crossing and short-sale constraints are important forces.

5.1 Exchange-Traded Funds

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. This lowers the power of our analysis. To assess whether embedded belief crossing nevertheless shows up in ETFs, we estimate the same pooled OLS regression as with CEFs on our sample of ETFs but replace the CEF premium (%) variable with the ETF premium (bps) variable.

The results are reported in Table 5. Consistent with embedded belief crossing helping explain ETF discounts, we obtain a coefficient estimate for *InvCov* of -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.

We conduct two additional sets of analyses regarding ETFs. First, as with CEFs, we compute for each ETF in each quarter, two measures of *InvCov*: one for the stock pairs that are in the top half based on their short-sale constraint, *High Constraint InvCov* and another for the stock pairs that are in the bottom half based on their short-sale constraint, *Low Constraint InvCov*. The results are shown in Table 6. Consistent with our prediction, *High Constraint InvCov* strongly associates with ETF discounts, while *Low Constraint InvCov* does not.

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. In our second set of additional analysts, we gauge the extent that authorized participants exploit discrepancies tied to changes in embedded belief-crossing. 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. We also first-difference our independent variables to reflect the fact that ETF flows respond to the change 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 Online Appendix Table A3. We find that 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%. 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.[12]

5.2 Mergers and Acquisitions

We next extend our tests to the corporate sector. We begin with M&As. 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 (in %). 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. The independent variables include *InvCov* and various controls as described in Table A1. *T*-statistics are based on standard errors clustered by year.

Table 7 Column 3, which reports our results when including our full set of controls, 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, which is consistent with our conjecture that belief crossing lowers the value of the whole relative to the sum of its parts even in M&As.

One alternative interpretation is that M&As for which beliefs cross—i.e., M&As for which the investor group that likes the acquirer (target) also happens to dislike the target (acquirer)—tend to create low synergies on average; hence, our observed low combined announcement day returns.

To assess the validity of this alternative interpretation, we conduct the following two tests. First, to the extent that synergies are reflected in subsequent operating performance, M&As with higher belief-crossing should produce worse operating

[12] 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 – appear to destabilize prices.

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. Within our framework, M&As with high embedded belief-crossing trade at a relative discount. M&As with high embedded belief-crossing may 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 embedded belief-crossing framework, Column (2) of Online Appendix Table A2 shows that an increase in 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 3.4% higher abnormal returns (t-statistic = 2.37) in the year following an M&A.

5.3 Conglomerates

For conglomerate firms, we follow prior studies (e.g., Lang and Stulz 1994) and 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 Table A1.

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 8 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.

5.4 Additional Analyses

In our final set of tests, we consider whether some managers are aware of the effect of embedded belief crossing and respond accordingly. We do so first for CEFs and ETFs and then for M&As.

Part of the "CEF puzzle" is that CEFs begin their lives trading at premia even though existing CEFs generally trade at significant discounts. Subsequently and fairly rapidly, such newly issued CEFs start trading at steep discounts also. Our framework cannot account for the phenomenon that CEFs begin their lives trading at premia. There are both behavioral (Lee, Shleifer and Thaler 1991) and rational explanations (Cherkes, Sagi, and Stanton 2008; Ross 2009) for this pattern. Our framework does predict though that to the extent that fund companies are aware of the negative effect of embedded belief crossing on portfolio value, managers initiating a CEF should construct portfolios with low levels of embedded belief crossing to maximize the proceeds from the IPO. Further, should managers find it difficult to construct such portfolios, they may forego the IPO altogether.

To test this idea, 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. We estimate a pooled logit regression, where 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.

Our evidence, shown in Online Appendix Table A6, reveals that higher industry-average belief crossing, indeed, forecasts fewer CEF/ETF IPOs. Specifically, our estimate for *InvCov* is -0.146 (t-statistic = -2.80). This implies that a one-standard-deviation increase in industry-average belief crossing lowers the likelihood of having at least one

CEF/ETF initiation by 3.3%, representing a 31.1% drop relative to the unconditional likelihood.

If at least some managers are aware of the negative effect of embedded belief crossing and respond accordingly, why then do we observe variation in the level of embedded belief crossing? Our answer is that all funds in our sample have investment themes. Thus, while it may be possible for a fund management company to market-time and only launch a fund if stocks in the corresponding theme have low levels of belief crossing with each other, once a fund is launched, managers have limited discretion in responding to changes in belief crossing while staying invested in stocks that fit the fund's overall theme. We believe that this can induce variation in belief crossing across funds and over time that is not tied to agency problems or weak advertising.

We conduct a similar experiment for M&As. M&As occur for a variety of reasons and firm managers may decide to conduct an M&A even if the level of embedded belief crossing is high. Still, on the margin, to the extent that firm managers recognize the negative valuation effect of embedded belief crossing, the likelihood of having an M&A between a firm pair 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 that are similar to the actual M&A pair along an array of observable firm characteristics, but that 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 the closest to the actual acquirer and target based on the propensity score matching approach utilizing firm size, book-to-market ratio, leverage, operating cash flow, ROA, G-index, idiosyncratic volatility and skewness.

In our first regression specification, we include the actual acquirer/target pair and also individually match the actual acquirer with each of the ten pseudo targets, resulting in one actual acquirer/target pair and 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, resulting again in one actual acquirer/target pair and ten counterfactual firm pairs. In our third regression specification, we include the 20 counterfactual firm pairs from above and, in addition, match each of the ten pseudo acquirers with each of the ten pseudo targets. Out of the resulting 120 pseudo pairs, we select the ten pseudo pairs whose pair level average firm characteristics are closest to the pair level average firm characteristics of the actual acquirer/target pair.[13]

We then estimate a logit regression, where 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 (both actual and pseudo). As shown in Online Appendix Table A7, we find that across all three regression specifications, high embedded belief crossing between firm pairs, indeed, lowers the probability of such firms merging. 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 lowers the likelihood of observing an M&A by nearly 3%, representing a 32.6% drop relative to the unconditional likelihood of an M&A.

6. Conclusion

In sum, our paper notes 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 that belief crossing is a broad and general force that helps explain a wide set of patterns across a full spectrum of securities. In addition to introducing a new construct, 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.

For future research, 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. 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

[13] Specifically, the ones that have the closest propensity score utilizing firm size, book-to-market ratio, leverage, operating cash flow, ROA, G-index, idiosyncratic volatility and skewness

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 Ferrell, 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 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 Table 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	-0.002	0.014	-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. 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 top-ten 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 belief crossing. We describe how we construct the remaining independent variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include fund-fixed effects in Column (1) and both fund- and year-quarter-fixed effects in Column (2). *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.

	(1)	(2)
InvCov	-0.552***	-0.491***
	(-2.80)	(-2.69)
Disagreement	0.180	0.388
	(0.36)	(0.91)
Crossing	0.105	0.034
	(0.58)	(0.19)
Inverse Price$_{pos}$	-1.693	-1.017
	(-1.08)	(-0.59)
Inverse Price$_{neg}$	-5.500***	-4.712***
	(-3.93)	(-2.61)
Dividend Yield$_{pos}$	1.820*	1.554
	(1.70)	(1.54)
Dividend Yield$_{neg}$	-0.481	-0.130
	(-1.04)	(-0.26)
Liquidity Ratio	0.902	1.372***
	(1.60)	(2.70)
Expense Ratio	0.910	0.925
	(1.05)	(1.07)
Excess Idiosyncratic Volatility	0.328	0.526
	(0.48)	(0.75)
Excess Skewness	0.090	0.135
	(0.68)	(1.23)
Fixed Effects	Fund	Fund and Time
# Obs.	1,906	1,906
Adj. R^2	0.828	0.843

Table 3. Closed-End Fund Discounts: The Role of Short-Sale Constraints

This table reports coefficient estimates from pooled OLS regressions of quarterly CEF premia on the interaction of a measure of short-sale constraints and a measure of investor disagreement and belief crossing across the CEF's top-ten 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 *Low Constraint InvCov* and *High Constraint InvCov* as follows: For each stock pair involving securities of the CEF's top-ten holdings, we compute a measure of short-sale constraints, which, in Columns (1) and (2), is (1-*IO*)***SI*, where *IO* is residual institutional ownership and *SI* is short interest. In Columns (3) and (4), it is the average daily lending fee in the corresponding quarter. Top-half stock pairs fall into the high constraint group; bottom-half stock pairs fall into the low constraint group. Within each group, for each stock pair, 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 *Low Constraint InvCov* (*High Constraint InvCov*) as the portfolio-weighted average *PairwiseCov* across all stock pairs in the low constraint group (high constraint group), multiplied by negative one. A large positive realization of *Low Constraint InvCov* (*High Constraint InvCov*) suggests a high level of belief crossing. We describe how we construct the remaining independent variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include fund-fixed effects in Columns (1) and (3) and both fund- and year-quarter-fixed effects in Columns (2) and (4). *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.

	Interaction of Residual Retail Ownership and Short Interest		Lending Fees	
	(1)	(2)	(3)	(4)
Low Constraint InvCov	-0.229	-0.155	0.126	0.060
	(-1.19)	(-0.69)	(0.82)	(0.32)
High Constraint InvCov	-0.408**	-0.351**	-0.385*	-0.392**
	(-1.97)	(-2.03)	(-1.81)	(-2.05)
Disagreement	0.489	0.628	0.188	0.409
	(0.90)	(1.30)	(0.40)	(0.98)
Crossing	0.037	-0.104	-0.100	-0.119
	(0.17)	(-0.43)	(-0.34)	(-0.38)
Institutional Ownership	0.356	0.734		
	(0.73)	(1.48)		
Short Interest	-0.752	-0.780		
	(-1.56)	(-1.54)		
Lending Fee			-0.204	-0.363
			(-0.75)	(-1.38)
Inverse Price$_{pos}$	-2.206	-1.472	-1.664	-0.951
	(-1.19)	(-0.74)	(-1.04)	(-0.55)
Inverse Price$_{neg}$	-5.894***	-5.221***	-5.470***	-4.704***
	(-3.72)	(-2.65)	(-3.87)	(-2.63)
Dividend Yield$_{pos}$	1.927*	1.440	1.796*	1.453
	(1.66)	(1.34)	(1.65)	(1.43)
Dividend Yield$_{neg}$	-0.456	-0.337	-0.429	-0.125
	(-0.95)	(-0.63)	(-0.92)	(-0.26)
Liquidity Ratio	1.284*	1.563***	0.932*	1.387***
	(1.69)	(2.63)	(1.65)	(2.74)
Expense Ratio	0.801	0.838	0.774	0.808
	(0.93)	(0.98)	(0.90)	(0.93)

Excess Idiosyncratic Volatility	0.369	0.590	0.301	0.536
	(0.52)	(0.79)	(0.43)	(0.75)
Excess Skewness	0.071	0.138	0.105	0.138
	(0.57)	(1.12)	(0.72)	(1.11)
Fixed Effects	Fund	Fund & Time	Fund	Fund & Time
# Obs.	1,906	1,906	1,885	1,885
Adj. R^2	0.794	0.812	0.827	0.842

Table 4. Closed-End Fund Discounts: Evidence from Broker Mergers and Closures

This table reports coefficient estimates from pooled OLS regressions of quarterly CEF premia on an indicator of whether a CEF's top-ten holdings are affected by a broker merger or closure. The dependent variable is the difference between the CEF's market price and the CEF's NAV, divided by the CEF's NAV [%]. For each broker merger-closure in our sample period, we consider all CEFs in the two quarters surrounding the merger/closure for Column (1) and the four quarters surrounding the merger/closure for Columns (2), respectively. *AffectedGroup* equals one if a CEF's top-ten holdings are affected by a broker merger-closure, and zero otherwise. *Post* equals one after a broker merger-closure, and zero otherwise. Thus, the observations here are at a broker merger-closure/CEF/year-quarter level. We describe how we construct the remaining independent variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include both fund- and event-fixed effects. *T*-statistics are reported in parentheses and are based on standard errors clustered by both fund and event. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Quarters Around Broker Merger or Closure	
	2 Quarters (1)	4 Quarters (2)
*AffectedGroup * Post*	0.519*	0.643**
	(1.86)	(2.28)
AffectedGroup	-0.380*	-0.276
	(-1.72)	(-1.20)
Post	-0.327*	-0.368
	(-1.65)	(-1.54)
Disagreement	0.344	0.460
	(0.96)	(1.34)
Crossing	-0.100	-0.119
	(-0.74)	(-0.78)
Inverse $Price_{pos}$	-2.891	-2.902**
	(-1.56)	(-2.00)
Inverse $Price_{neg}$	-5.431***	-5.150***
	(-2.82)	(-2.95)
Dividend $Yield_{pos}$	2.770**	2.783***
	(2.43)	(2.87)
Dividend $Yield_{neg}$	0.192	0.046
	(0.38)	(0.10)
Liquidity Ratio	1.073**	1.062**
	(2.24)	(2.25)
Expense Ratio	1.073	1.313
	(1.07)	(0.94)
Excess Idiosyncratic Volatility	0.769*	0.905***
	(1.74)	(2.79)
Excess Skewness	0.214	0.175
	(1.39)	(1.31)
Fixed Effects	Fund and Event	Fund and Event
# Obs.	9,948	12,752
Adj. R^2	0.850	0.851

Table 5. The Effect of Belief Crossing in Other Settings: Exchange-Traded Funds

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 top-ten holdings. The dependent variable is the difference between the ETF's market price and the ETF's NAV, divided by the ETF's NAV [in basis point]. 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 belief crossing. We describe how we construct the remaining independent variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include fund-fixed effects in Column (1) and both fund- and year-quarter-fixed effects in Column (2). *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.

	(1)	(2)
InvCov	-1.639***	-1.465**
	(-2.65)	(-2.24)
Disagreement	0.096	0.582
	(0.08)	(0.47)
Crossing	0.105	0.034
	(0.58)	(0.19)
Inverse Price$_{pos}$	0.666	0.505
	(1.57)	(1.04)
Inverse Price$_{neg}$	-5.500***	-4.712***
	(-3.93)	(-2.61)
Dividend Yield$_{pos}$	8.266***	3.683
	(2.73)	(0.83)
Dividend Yield$_{neg}$	-0.481	-0.130
	(-1.04)	(-0.26)
Liquidity Ratio	-6.606**	-10.344**
	(-2.15)	(-2.02)
Expense Ratio	0.910	0.925
	(1.05)	(1.07)
Excess Idiosyncratic Volatility	1.688*	1.822
	(1.85)	(1.30)
Excess Skewness	0.090	0.135
	(0.68)	(1.23)
Fixed Effects	Fund	Fund and Time
# Obs.	4,310	4,310
Adj. R^2	0.337	0.372

Table 6. Exchange-Traded Fund Discounts: The Role of Short-Sale Constraints

This table reports coefficient estimates from pooled OLS regressions of quarterly ETF premia on the interaction of a measure of short-sale constraints and a measure of investor disagreement and belief crossing across the ETF's top-ten 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 *Low Constraint InvCov* and *High Constraint InvCov* as follows: For each stock pair involving securities of the ETF's top-ten holdings, we compute a measure of short-sale constraints, which, in Columns (1) and (2), is (1-*IO*)**SI*, where *IO* is residual institutional ownership, and *SI* is short interest. In Columns (3) and (4), it is the average daily lending fee in the corresponding quarter. Top-half stock pairs fall into the high constraint group; bottom-half stock pairs fall into the low constraint group. Within each group, for each stock pair, 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 *Low Constraint InvCov* (*High Constraint InvCov*) as the portfolio-weighted average *PairwiseCov* across all stock pairs in the low constraint group (high constraint group), multiplied by negative one. A large positive realization of *Low Constraint InvCov* (*High Constraint InvCov*) suggests a high level of belief crossing. We describe how we construct the remaining independent variables in Appendix A1. All independent variables are normalized to have a standard deviation of one. We include fund-fixed effects in Columns (1) and (3) and both fund- and year-quarter-fixed effects in Columns (2) and (4). *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.

	Interaction of Residual Retail Ownership and Short Interest		Lending Fees	
	(1)	(2)	(3)	(4)
Low Constraint InvCov	0.889	1.599	-0.170	-0.172
	(0.38)	(0.60)	(-0.81)	(-0.83)
High Constraint InvCov	-2.686***	-2.661***	-1.437**	-1.473**
	(-4.57)	(-3.78)	(-2.07)	(-2.05)
Disagreement	0.020	0.413	0.395	0.470**
	(0.02)	(0.35)	(1.51)	(1.99)
Crossing	0.535	0.335	0.503**	0.450**
	(1.08)	(0.61)	(2.48)	(2.18)
Institutional Ownership	0.675	-0.249		
	(0.53)	(-0.19)		
Short Interest	1.637*	2.929**		
	(1.65)	(2.05)		
Lending Fees			-0.068	-0.070
			(-0.56)	(-0.65)
Inverse Price$_{pos}$	8.208***	3.537	4.614***	4.089***
	(2.71)	(0.79)	(9.98)	(4.47)
Inverse Price$_{neg}$	-6.748**	-10.577**	-4.315***	-4.420***
	(-2.19)	(-2.05)	(-5.91)	(-3.93)
Dividend Yield$_{pos}$	1.629*	1.316	1.486 ***	1.410***
	(1.79)	(1.27)	(4.66)	(4.36)
Dividend Yield$_{neg}$	-3.642***	-3.526***	-1.255***	-1.184***
	(-3.24)	(-3.30)	(-4.91)	(-4.54)
Liquidity Ratio	-2.253	-2.061	-0.348	-0.199
	(-1.26)	(-1.24)	(-0.98)	(-0.70)
Expense Ratio	-1.314	-1.645	0.622	0.598
	(-0.57)	(-0.63)	(0.77)	(0.80)

Excess Idiosyncratic Volatility	-0.235	0.569	0.218	0.116
	(-0.35)	(0.63)	(1.05)	(0.41)
Excess Skewness	1.879	2.268	0.080	0.086
	(0.53)	(0.62)	(0.42)	(0.46)
Fixed Effects	Fund	Fund and Time	Fund	Fund and Time
# Obs.	4,310	4,310	4,301	4,301
Adj. R^2	0.338	0.374	0.631	0.659

Table 7. The Effect of Belief Crossing in Other Settings: Mergers and Acquisitions

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 belief crossing. We describe how we construct the remaining independent 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.

	(1)	(2)	(3)
InvCov	-1.424***	-1.665***	-1.713***
	(-3.93)	(-4.62)	(-4.72)
Disagreement	-0.350	-0.652*	-0.763**
	(-1.03)	(-1.81)	(-2.11)
Crossing	-0.013	0.163	0.215
	(-0.04)	(0.46)	(0.61)
Acquirer Characteristics:			
ln(Acquirer Market Cap)		-2.610***	-1.382
		(-5.51)	(-1.42)
Acquirer Market-to-Book Ratio		0.568	0.618
		(1.43)	(1.51)
Acquirer ROA		0.387	0.321
		(0.72)	(0.60)
Acquirer Leverage		-0.164	-0.081
		(-0.33)	(-0.16)
Acquirer Operating Cash Flow		-0.562	-0.723
		(-1.04)	(-1.22)
Acquirer ATP Index		-0.294	-0.131
		(-0.60)	(-0.27)
Target Characteristics:			
ln(Target Market Cap)		1.070**	0.050
		(2.43)	(0.06)
Target Market-to-Book Ratio		-0.395	-0.416
		(-1.05)	(-1.12)
Target ROA		1.267**	1.284**
		(2.13)	(2.13)
Target Leverage		-0.048	0.322
		(-0.11)	(0.70)
Target Operating Cash Flow		-1.355**	-1.333**
		(-2.38)	(-2.37)
Target ATP Index		0.574	0.780
		(0.58)	(0.79)

Table 7. Continued.

	(1)	(2)	(3)
Deal Characteristics:			
Relative Size			-1.596**
			(-2.12)
Combined Idiosyncratic Volatility			0.415
			(0.78)
Combined Skewness			-0.123
			(-0.35)
Tender Offer			-0.650
			(-0.61)
Hostile Offer			2.249
			(0.73)
Competing Offers			1.650
			(0.83)
Cash Only			2.964***
			(3.41)
Stock Only			-0.551
			(-0.62)
Same Industry			0.600
			(0.81)
Fixed Effects	Time	Time	Time
# Obs.	405	405	405
Adj. R^2	0.175	0.272	0.314

Table 8. The Effect of Belief Crossing in Other Settings: 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 independent 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) Pooled	(2) Fama-MacBeth
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

Figure 1a. Sources of Information for Investors: A Fund's Website

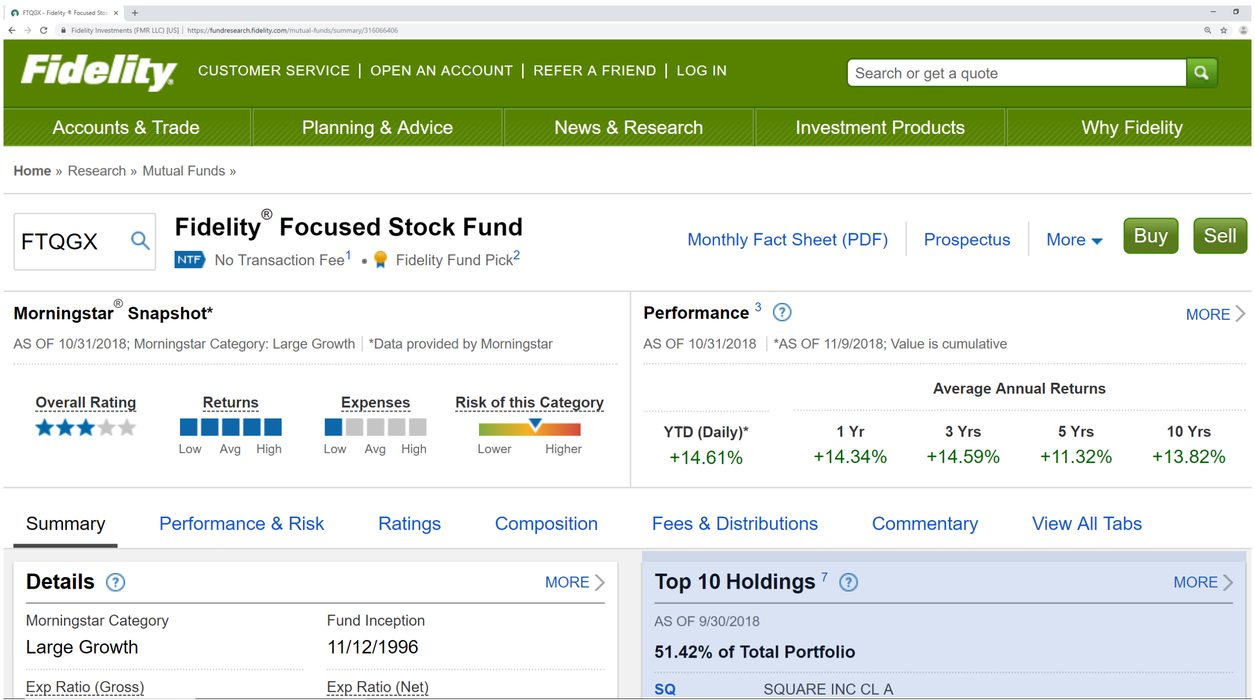


Figure 1b. Sources of Information for Investors: Other Investment Related Website

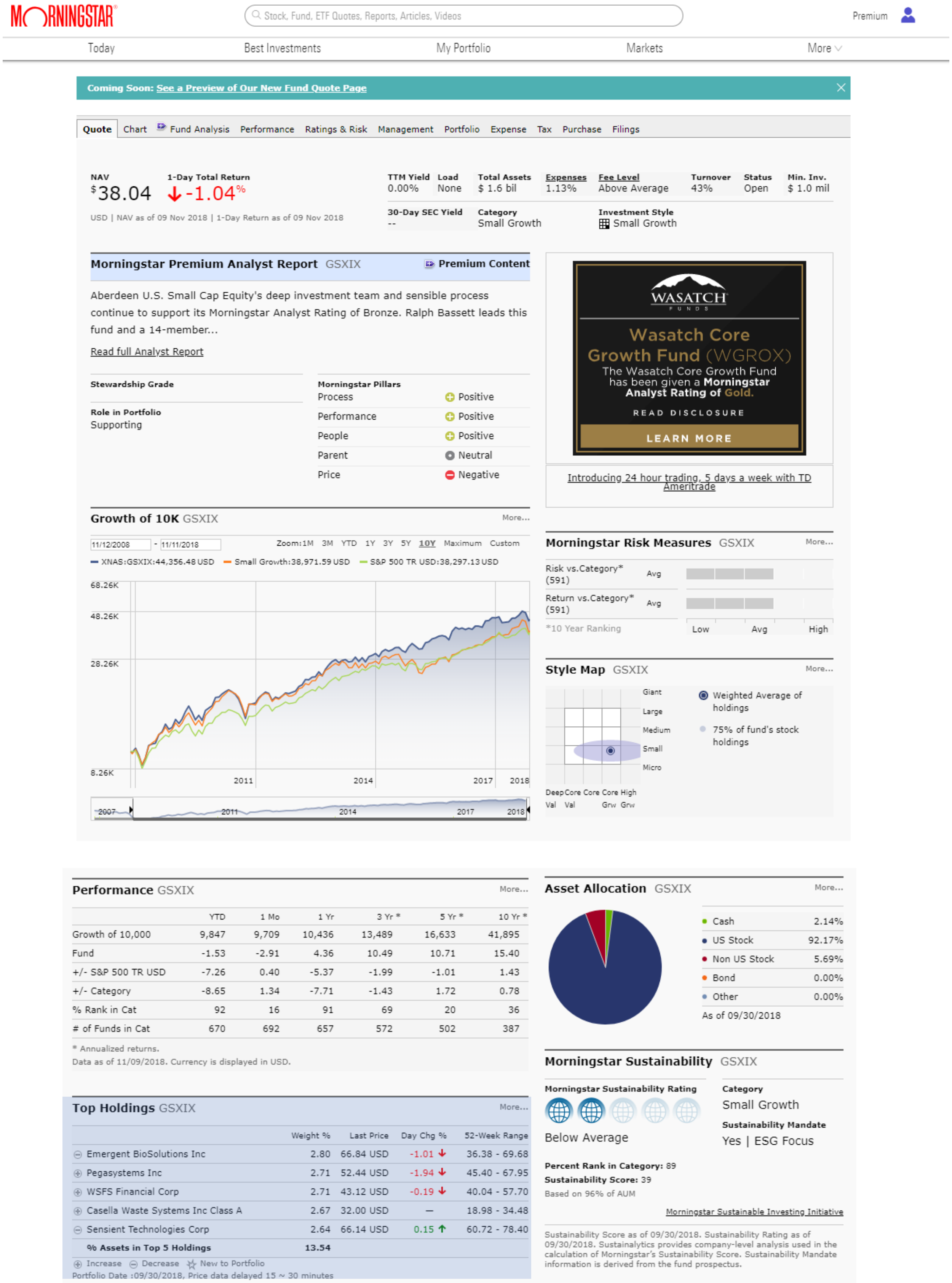


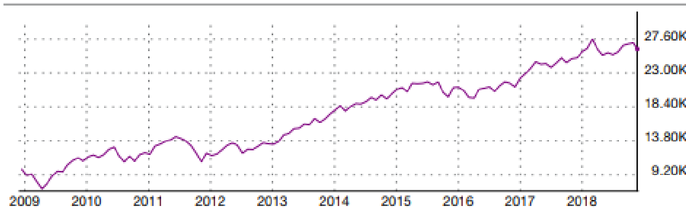
Figure 1c. Sources of Information for Investors: A Fund's Fact Sheet

Fidelity® Blue Chip Value Fund (FBCVX)

NTF No Transaction Fee[1]

Hypothetical Growth of $10,000[2,3] (10/31/2008-10/31/2018)

■ Fidelity® Blue Chip Value Fund $26,004



The performance data featured represents past performance, which is no guarantee of future results. Investment return and principal value of an investment will fluctuate; therefore, you may have a gain or loss when you sell your shares. Current performance may be higher or lower than the performance data quoted.

Morningstar® Snapshot*[4]

(AS OF 9/30/2018)

Morningstar Category	Large Value
Risk of this Category	LOWER HIGHER
Overall Rating	★★☆☆☆
Returns	LOW AVG HIGH
Expenses	LOW AVG HIGH

*Data provided by Morningstar

Performance[3,5,6]

Monthly (AS OF 10/31/2018)	YTD (Monthly)	Average Annual Total Returns 1 Yr	3 Yrs	5 Yrs	10 Yrs	Life
Fidelity® Blue Chip Value Fund	-1.25%	3.86%	7.33%	8.35%	10.03%	6.45%
Russell 1000 Value	-1.46%	3.03%	8.88%	8.61%	11.30%	8.18%
Quarter-End (AS OF 9/30/2018)						
Fidelity® Blue Chip Value Fund		8.67%	11.08%	10.11%	8.10%	6.77%

Equity StyleMap®*[7]

(AS OF 9/30/2018)

Large Value
*91.4% Fund Assets Covered

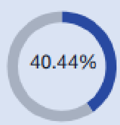
Calendar Year Returns[3,5]

(AS OF 10/31/2018)

	2014	2015	2016	2017	2018
Fidelity® Blue Chip Value Fund	13.19%	-1.96%	11.19%	14.87%	-1.25%
Russell 1000 Value	13.45%	-3.83%	17.34%	13.66%	-1.46%

Top 10 Holdings[8]

(AS OF 9/30/2018)



BERKSHIRE HATHAWAY INC CL B
CVS HEALTH CORP
CIGNA CORP
WELLS FARGO & CO
AMGEN INC
COMCAST CORP CL A
EXXON MOBIL CORP
US BANCORP DEL
TWENTY FIRST CENTURY FOX INC-A
ANTHEM INC

% of Total Portfolio: 40.44%
45 holdings as of 9/30/2018
45 issuers as of 9/30/2018

Details

Fund Inception	6/17/2003
NAV on 10/31/2018	$19.16
Exp Ratio (Gross) 9/29/2018	0.7%
Exp Ratio (Net) 9/29/2018	0.7%
Minimum to Invest[12]	$0.00
Turnover Rate 7/31/2018	45%
Portfolio Net Assets ($M) 10/31/2018	$387.48