Skewness Consequences of Seeking Alpha

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Mutual funds seek alpha, but coskewness is also an important performance attribute. Coskewness of fund returns is associated with market timing, liquidity management, and derivative use. Measures of active management associated with positive alphas are also associated with undesirable coskewness. When controlling for other characteristics, coskewness is positively associated with activity measures related to market timing and negatively associated with activity measures related to stock picking. In the cross-section of funds, the latter effect dominates, so funds generate undesirable coskewness in the pursuit of alpha. Money flows to funds with desirable coskewness. (*JEL* G11, G20, G23)

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Mutual fund performance is often measured by alpha relative to a benchmark (Jensen 1969). This makes sense for quadratic utility investors, because mean-variance efficiency can be improved by a marginal investment in a positive alpha fund (Dybvig and Ross 1985). However, there is evidence that investors care about moments beyond mean and variance, in particular that investors prefer positive skewness.[1] For these investors, the marginal effect of an investment in a mutual fund on the investor's portfolio skewness is also important. For an

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[1] Golec and Tamarkin (1998) and Garrett and Sobel (1999) explain horse track betting and lottery participation through skewness preferences. Kumar (2009) links skewness preferences to individual investors' stock decisions, showing that those that play the lottery also choose stocks with positive idiosyncratic skewness. Goetzmann and Kumar (2008) show that individuals who hold undiversified portfolios hold stocks with high levels of skewness,

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investor who holds the market, the marginal effect depends on coskewness with the market return. Absent investment skill, theory (e.g., Kraus and Litzenberger 1976) suggests that managers should not be able to produce both desirable alpha and coskewness. Consistent with this and prior empirical work by Moreno and Rodríguez (2009), we document a robust trade-off between CAPM alphas and coskewness in the cross-section of fund returns: funds with higher alphas tend to have lower (worse) coskewness and vice versa.

We study the determinants of mutual fund coskewness. There are at least three possible sources of coskewness in fund returns that are distinct from the coskewness of stocks held by the funds. One is market timing. Funds that successfully time the market create return profiles that are convex in the market return (Treynor and Mazuy 1966)—effectively, they create protective puts at no cost—and hence have positive coskewness with the market. We account for market timing in two ways. First, we estimate how market exposure varies over time based on public information (Ferson and Schadt 1996) and flows (Edelen 1999) and we decompose coskewness into a part that is due to time-varying market exposures and a part that is due to other factors. Second, we infer the market timing return of each fund using the calculation of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and show that it is positively related to coskewness as expected. A second source of coskewness is cash management. If money flows into funds when expected returns are high and it takes some time for funds to invest new cash, then funds will be holding more cash when expected returns are high. This implies that their return profiles will be concave in the market return and hence have negative coskewness with the market.[2] We show that coskewness is worse for funds that have more illiquid noncash holdings. This is consistent with such funds taking longer to invest new cash when expected returns are high. Furthermore, funds that hold more cash in general suffer less from illiquidity. A third source is that some funds use derivatives. For example, selling covered calls produces a return profile that is concave in the market return and hence has negative coskewness with the market.[3] We find that funds' use of options on individual stocks and their use of options on stock indices and stock index futures contribute significantly to coskewness. The evidence is consistent with funds writing covered calls on

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and Bailey, Kumar, and Ng (2011) show that individual investors also tend to choose mutual funds that hold stocks with high levels of skewness. Heuson, Hutchinson, and Kumar (2016) show that hedge funds with more skewed returns receive greater capital flows. Consistent with Goetzmann and Kumar (2008), Mitton and Vorkink (2007) show that the prevalence of undiversified portfolios can be explained by heterogeneous preferences for skewness.

[2] Ferson and Schadt (1996) and Ferson and Warther (1996) point out that delays in investing cash when expected returns are high can generate negative market timing.

[3] Jagannathan and Korajczyk (1986) point out that the use of options by funds can be misinterpreted as market timing and show that options would generate a negative relation between CAPM alphas and coskewness if returns were iid. See also Leland (1999), who points out that selling calls produces negative coskewness and positive CAPM alphas when there is a representative investor with constant relative risk aversion. Thus, selling calls can be a strategy to produce alpha at a coskewness cost.

individual stocks (generating negative coskewness) and buying protective puts on the market (generating positive coskewness).

Recent work on mutual fund performance has shown that various characteristics of funds predict performance, when performance is measured by alpha. We show that the same characteristics that predict positive alphas also predict undesirable coskewness with the market. We sort funds by Industry concentration (Kacperczyk, Sialm, and Zheng 2005), Return gap (Kacperczyk, Sialm, and Zheng 2008), Active share (Cremers and Petajisto 2009), $1-R^2$ (Amihud and Goyenko 2013), a time-varying Skill index (Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014), and Active weight (Doshi, Elkamhi, and Simutin 2015). In each case, higher alpha portfolios have worse coskewness.

To determine the relative importance of different sources of coskewness, we run a cross-sectional regression of coskewness on a variety of fund characteristics. Controlling for other activities, coskewness is positively related to Market timing (a component of the Skill index), Active weight, and Industry concentration. The positive coefficient on Market timing is expected, because successful market timing creates a convex return profile, as discussed above. The positive coefficients on Active weight and Industry concentration suggest that these characteristics are also related to market timing.[4] Together, these three variables account for 15% of the explained variation in coskewness. Variables related to cash management (illiquidity of holdings and abnormal cash holdings) explain an additional 7%. Derivatives usage and other disclosed activities account for 5% of the explained variation in coskewness. Stock selection, either dynamic or passive, explains the bulk of the remaining explained variation. Dynamic selection activities like turnover and Active share contribute negatively to coskewness, accounting for 15% of the explained variation in coskewness. Finally, the chosen fund style is an important determinant of coskewness. About half of the explained variation is due to the underlying styles of the funds.

There is a clear trade-off between CAPM alphas and coskewness in the cross-section of fund returns: funds with higher alphas tend to have lower (worse) coskewness and vice versa. This trade-off cannot be generated by the first two sources of coskewness described above. Successful market timers create positive alphas and positive coskewness. Funds that have a greater need to hold cash when the market risk premium is high suffer both in average returns and in coskewness. So, each of the first two sources of coskewness would produce a positive relation between alphas and coskewness. The third source would create a negative relation under the assumptions of Jagannathan and Korajczyk (1986) and Leland (1999); however, only 24% of the funds in our sample report using options on equities, equity indices, or equity index futures.

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[4] We find additional evidence to this effect in our analysis of characteristic-sorted portfolios.

The fact that the relation between fund alphas and coskewness is negative suggests that it is predominantly driven by stock picking (other unobserved activities of mutual funds could also contribute to the relation; for example, funds could create synthetic options by dynamic trading). The presence of a trade-off between alpha and coskewness among stocks is implied by the coskewness pricing model (Kraus and Litzenberger 1976) and has been documented by Kraus and Litzenberger (1976), Harvey and Siddique (2000), Dittmar (2002), Guidolin and Timmermann (2008), and Christoffersen et al. (2016). In fact, portfolios formed from sorts on stock picking characteristics, such as Active share and $1-R^2$, exhibit larger estimated trade-offs than what we observe for stock portfolios on average, indicating that funds that are active in stock picking tend to pick stocks whose high (conditional) alphas carry especially high coskewness costs.[5]

We control for styles throughout. Harvey and Siddique (2000) show that styles associated with CAPM alphas are related to coskewness. Furthermore, standard style factors (SMB, HML, and UMD) exhibit a trade-off between alpha and coskewness: each has a positive alpha and negative coskewness. Styles account for some of the trade-off between alpha and coskewness in mutual fund returns, but the trade-off is significant even controlling for styles.

If retail investors do not monitor coskewness (even though their utilities ultimately depend on it because they are not quadratic), then there is scope for active funds to exploit the trade-off the market presents, producing alpha at a coskewness cost. We show that fund flows do respond to coskewness in addition to responding to alphas.[6] However, the flow response to coskewness is weaker among funds that serve fewer institutional investors, so some retail investors are apparently less aware of or at least less concerned about coskewness. This is consistent with funds having scope to exploit the trade-off between alpha and coskewness available in the market.

We assess the importance of mutual fund coskewness both empirically and theoretically. Empirically, the difference in alpha between the bottom and top coskewness quartiles of funds is 4.8% per year, which is clearly economically meaningful. Furthermore, we use standard sets of stock portfolios to estimate the price of coskewness and conclude that a one-standard-deviation change in coskewness (based on the standard deviation across funds) is equivalent to a change in alpha of around 2.5% per year. For the theoretical assessment, we follow Dahlquist, Farago, and Tédongap (2017) in modeling return skewness via exponential-lognormal distributions and in assuming investors have the

[5] Trade-offs of different magnitudes could arise in several ways. The coskewness pricing model could hold conditionally with a time-varying price of coskewness. Alternatively, the trade-off could be nonlinear, which is a generalization of the coskewness pricing model.

[6] We look at flow responses to coskewness with the market and to CAPM alphas. Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) show that mutual fund investors respond to CAPM alphas more than to alphas calculated under other benchmarks.

generalized disappointment aversion preferences of Routledge and Zin (2010). We find that our estimated price of coskewness is consistent with this model for reasonable parameter values. For the fund characteristics associated with abnormal performance, we adjust CAPM alphas of the high-minus-low portfolios by penalizing negative coskewness and rewarding positive coskewness based on the price of coskewness. The adjusted alpha is significant only for Active weight (Doshi, Elkamhi, and Simutin 2015). We conclude that Active weight is a characteristic that signals outperformance even when coskewness costs are considered.

Moreno and Rodríguez (2009) also incorporate coskewness in mutual fund performance evaluation. They create a coskewness factor by sorting stocks based on coskewness with the market and following a procedure similar to that used by Fama and French (1993) to construct SMB and HML.[7] One important difference between their paper and ours is that they study exposure to their coskewness factor whereas we study coskewness characteristics of mutual funds. We focus on the coskewness characteristic because we assume investors care about skewness and we are interested in the value that funds do or do not create for investors. Moreno and Rodríguez include the coskewness factor with the market and also with the Fama-French-Carhart (FFC) factors and compute mutual fund alphas. The price of their factor would be the price of coskewness if their factor were the portfolio return most highly correlated with the squared market return. Because the factor has essentially an ad hoc construction, the price of the factor may be less than the true price of coskewness (our estimate of the price of coskewness may also be biased downward due to an errors-in-variables attenuation bias). Moreno and Rodríguez show a trade-off between exposure to the factor and alphas. They also provide some analyses relating fund coskewness to fund size, expenses, turnover, and coarse investment categories. However, they do not study the fund characteristics recently shown to predict alphas, they do not study how flows respond to coskewness, and they do not study market timing, the effect of cash management on coskewness, or the use of derivatives by funds.

1. Coskewness: Definition and Estimation

1.1 Definition of coskewness

Coskewness is the covariance of a return or excess return with a squared benchmark return. We use the market as the benchmark. Let R_m denote the market return, and let R_f denote the risk-free return. Given a return R, project its excess return on the market excess return as usual:

$$R-R_f=\alpha+\beta(R_m-R_f)+\varepsilon. \tag{1}$$

[7] Moreno and Rodríguez (2006) perform a related analysis using a stochastic discount factor (SDF) approach for Spanish mutual funds.

The random variable $\alpha+\varepsilon$ is the payoff of a zero-cost portfolio, which is an excess return. We define coskewness based on it as

$$\mathrm{cov}(\alpha+\varepsilon,(R_m-R_f)^2)=\mathsf{E}[\varepsilon(R_m-R_f)^2]. \tag{2}$$

To see why coskewness should matter to an investor, consider a return R and a constant $\nu\geq 0$ and construct the return

$$R_\nu = R_m+\nu[R-R_f-\beta(R_m-R_f)] = R_m+\nu[\alpha+\varepsilon]. \tag{3}$$

This is the benchmark combined with an investment in a zero-beta version of R. The derivatives of the first three moments of R_ν with respect to ν evaluated at $\nu=0$ are

$$\left.\frac{\mathrm{d}\bar{R}_\nu}{\mathrm{d}\nu}\right|_{\nu=0}=\alpha, \tag{4a}$$

$$\left.\frac{\mathrm{d}\,\mathrm{var}(R_\nu)}{\mathrm{d}\nu}\right|_{\nu=0}=0, \tag{4b}$$

$$\left.\frac{1}{3}\cdot\frac{\mathrm{d}\mathsf{E}[(R_\nu-\bar{R}_\nu)^3]}{\mathrm{d}\nu}\right|_{\nu=0}=\mathsf{E}[\varepsilon(R_m-R_f)^2]. \tag{4c}$$

The derivatives tell us the signs of the changes in the first three return moments produced by a small investment in the return, relative to holding the market. From (4a), we see that the investment increases the mean return if the alpha is positive. From (4b), we see that the investment has only a second-order effect on variance. Thus, a marginal investment in a return with a positive alpha can improve mean-variance efficiency (Dybvig and Ross 1985). From (4c), we see that a marginal investment in the return increases skewness if the return has positive coskewness. Therefore, a marginal investment in a return with a positive alpha and positive coskewness can improve mean-variance-skewness efficiency.

If investors care only about the first three moments of returns, then there should be an exact negative linear relation between the CAPM alpha and coskewness. This is the coskewness pricing model (Kraus and Litzenberger 1976). See Appendix A for a derivation of this trade-off from the coskewness pricing model. More generally, if investors care about more than the first two moments of returns, then there should generally be a negative (and possibly nonlinear) relation between alphas and coskewness, as long as investors have decreasing absolute risk aversion and hence like both the first and third moments.

We interpret the trade-off between alpha and residual coskewness as a cost of seeking alpha. This trade-off also could be viewed as an alpha cost to seeking positive coskewness. Since it is well established that fund managers have the incentive to "seek alpha," we believe the former interpretation is most natural. The majority of tests, with the exception of those in Table IA.2, which regresses average returns on coskewness and other factor loadings, reflect this view by estimating the coskewness costs of seeking alpha.

1.2 Relation of coskewness to market timing measures

A closely related measure of coskewness is obtained from the quadratic regression

$$R-R_f=a+b_1(R_m-R_f)+b_2(R_m-R_f)^2+\epsilon. \tag{5}$$

Note that a and b_1 from (5) are not equivalent to α and β from (1). It follows from the Frisch-Waugh Theorem that the multivariate regression coefficient b_2 equals the coskewness defined in (2) multiplied by a positive factor that depends on moments of the market return. See Appendix A for further detail on the relation between b_2 and coskewness from (2). The quadratic regression (5) is the regression of Treynor and Mazuy (1966), who interpret $b_2>0$ as an indication of successful market timing. Because the funds in our sample operate over different time periods, the market moments relating b_2 to coskewness (2) will be different for different funds; hence, the two parameters will not be proportional to each other empirically in the cross-section of funds. Because of the importance of coskewness (2) shown in (4c), we calculate it instead of b_2. However, qualitative cross-sectional results for one parameter also will be generally true for the other. When we reference work from the market timing literature, we generally refer to estimates of b_2 as coskewness.

A persistent finding in the market timing literature is that $b_2<0$ for many funds, indicating "perverse" market timing ability by fund managers. Many papers argue that b_2 is a poor measure of market timing for various reasons. For instance, b_2 can be affected by time-varying betas (Edelen 1999; Ferson and Schadt 1996; Ferson and Warther 1996), it can be affected by the use of options or stocks exhibiting option-like features (Jagannathan and Korajczyk 1986), and it is affected by dynamic trading between return measurement dates (Pfleiderer and Bhattacharya 1983). In general, the market timing literature has not considered the implications of the coskewness pricing model in its relation to b_2. We are aware of only one exception, the study of market timing in bond funds by Chen, Ferson, and Peters (2010), which briefly mentions that the quadratic coefficient also has the interpretation as coskewness.

More recent papers in the market timing literature make use of holdings-based measures (Jiang, Yao, and Yu 2007; Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014). As discussed in the introduction, successful market timing should result in a positive correlation between alpha and coskewness, rather than the negative correlation documented in Section 2. In Section 3, we show that the holdings-based market-timing measure of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) is positively related to coskewness when we control for other fund activities.

1.3 Data

We use daily net returns data from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. We merge the daily fund data to holdings data from Thomson Reuters using the WRDS MF Links file. For a given fund, we consider average returns across share classes, weighting by total net assets in each class. The sample contains active domestic equity mutual funds.[8] We exclude index and target date funds. To account for the incubation bias documented by Evans (2010), we only include fund returns for dates later than the fund's reported first offer date and for dates for which the fund name is not missing in the CRSP dataset. We also exclude any funds whose total net assets are below \$15 million or that hold fewer than ten stocks in each reporting period. Our analysis includes holdings-based style categories following Daniel et al. (1997) and Wermers (2003) (described in Section 2.3) and holdings-based attribution analyses (described in Section 2.4). The sample excludes any funds for which we cannot determine these values. We exclude funds with fewer than 60 days of returns. We also exclude any fund for which less than 90% of the daily observations in CRSP contain reported returns, which eliminates funds that report returns weekly rather than daily. The sample runs from September 1, 1998 through June 30, 2014, and includes 3,001 funds. The sample starts in 1998 as this is the initiation of daily return reporting for mutual funds by CRSP.

We also study stock portfolios formed from sorts on characteristics that have been shown to spread returns. We use the same sample horizon as the mutual fund sample. We obtain benchmark market excess returns and risk-free returns from Kenneth French's Web site.[9] We use several portfolios from French's Web site, specifically the 100 Fama-French portfolios formed by bivariate sorts on size and book-to-market, investment, or profitability as well as the 25 size and momentum portfolios. We use CRSP daily and monthly stock returns for various holdings-based measures described throughout the text.

1.4 Estimation of coskewness

For each asset i, we estimate α_i and β_i by OLS from the usual regression equation (1). Let γ_i denote coskewness. Given a sample of size T_i, we estimate coskewness as

$$\widehat{\gamma_i} = \frac{1}{T_i} \sum_{t=1}^{T_i} \varepsilon_{it} (R_{mt} - R_{ft})^2, \tag{6}$$

where the ε_{it} are the fitted residuals from the regression (1). For most of our results, we estimate the regression (1) and coskewness (6) once for each asset, using the full time series available for the asset. However, we also allow for time variation in parameters by estimating rolling regressions using 5 years of daily data in each regression.

[8] This corresponds to CRSP objective codes with "E" in the first position, "D" in the second position, and "C" or "Y" in the third position. We exclude any hedged or short funds (third/fourth positions of "YH" or "YS") as well as option income funds (si_obj_code of "OPI").

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.

Table 1
Distributions of point estimates of alpha and coskewness

A. Static estimates

	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$
10th	−1.74	−0.30	0.70
25th	−0.76	−0.18	0.87
Median	0.11	−0.06	0.97
75th	0.98	0.03	1.06
90th	1.86	0.10	1.16
IQRange	1.75	0.21	0.19
SD	1.59	0.17	0.20
Distribution of point estimates			
	$\hat{\gamma}>0$	$\hat{\gamma}<0$	Total
$\hat{\alpha}>0$	9.23	43.89	53.12
$\hat{\alpha}<0$	23.26	23.63	46.88
Total	32.49	67.51	100.00

B. Time-varying estimates

	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$
10th	−1.50	−0.39	0.68
25th	−0.70	−0.17	0.88
Median	0.10	−0.04	0.98
75th	1.11	0.02	1.06
90th	2.56	0.10	1.16
IQRange	1.81	0.19	0.19
SD	1.81	0.20	0.21
Distribution of point estimates			
	$\hat{\gamma}>0$	$\hat{\gamma}<0$	Total
$\hat{\alpha}>0$	12.22	41.14	53.36
$\hat{\alpha}<0$	20.11	26.53	46.64
Total	32.33	67.67	100.00

In panel A, alpha, coskewness (γ), and beta are estimated for 3,001 active mutual funds over the time period September 1, 1998 through June 30, 2014, using the full sample of daily returns. In panel B, alpha, coskewness (γ), and beta are estimated using rolling regressions over 5 years of data. The rolling regressions use overlapping windows that roll forward daily. $\hat{\alpha}$ is measured in basis points (*bps*) per day, and coskewness $\hat{\gamma}$ is measured in $\%^3$ per day.

2. The Trade-off between Alpha and Coskewness

In this section, we show that alpha and coskewness are negatively related in the cross-section of mutual fund returns. We decompose alphas into an alpha due to average holdings and the residual, which is due to trading. Both parts are negatively related to coskewness. When we sort stocks by activity measures shown previously to predict alphas, we find that higher alpha portfolios have worse coskewness. These results are robust to controlling for styles.

2.1 Coskewness costs of funds

First, we report the distribution of alpha and coskewness estimates for our sample. Table 1 reports summary statistics for funds over the full time-series (panel A) and for funds over 5-year windows rolling forward daily (panel B). Coskewness is negative for 68% of the funds, consistent with prior evidence by Moreno and Rodríguez (2009) that the median fund has negative

Table 2
Coskewness costs of alpha: Funds and stocks

A. Coskewness cost per unit of α: Static estimates

		Stock portfolios			
	Mutual funds	FF size/BM	FF size/inv	FF size/mom	FF size/profit
	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$
$\hat{\alpha}$	−3.39***	−3.89**	−4.22***	−7.28***	−3.78**
	(−12.38)	(−2.11)	(−2.80)	(−5.74)	(−2.42)
Constant	−0.09***	−0.16***	−0.13***	−0.02	−0.12***
	(−28.75)	(−3.88)	(−3.42)	(−0.52)	(−3.22)

B. Coskewness cost per unit of α: Rolling estimates

		Stock portfolios			
	Mutual funds	FF size/BM	FF size/inv	FF size/mom	FF size/profit
	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$
$\hat{\alpha}$	−2.11***	−2.04***	−1.18***	−1.67***	−1.00***
	(−8.77)	(−8.14)	(−4.78)	(−2.95)	(−3.83)
Constant	−0.09***	−0.19***	−0.18***	−0.10	−0.17***
	(−2.63)	(−3.50)	(−3.04)	(−1.52)	(−2.63)

Alpha and coskewness (γ) are estimated for active mutual funds and stock portfolios over the time period September 1, 1998 through June 30, 2014, using daily returns. Point estimates for funds are winsorized at 1% and 99%. $\hat{\alpha}$ is measured in % per day, and coskewness $\hat{\gamma}$ is measured in $\%^3$ per day. The table reports cross-sectional regressions of coskewness on alpha for mutual funds and stock portfolios: $\hat{\gamma}_i = A + B\hat{\alpha}_i + e_i$. There are 3,001 active mutual funds. There are 25 Fama-French (FF) size and momentum portfolios and 100 Fama-French portfolios for each of the remaining classifications. Each column of panel A presents results from a cross-sectional regression of coskewness on alpha estimated over the full time-series. Panel B presents the time-series means of regression coefficients obtained from daily cross-sectional regressions using the alpha and coskewness estimates from rolling 5-year time-series regressions. t-statistics are reported in parentheses. The standard errors of the daily estimates are corrected for 1,260 (5 years of) lags of autocorrelation. Statistical significance is represented by * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

coskewness. It is also consistent with the persistent finding in the market timing literature that $b_2 < 0$ for most funds. The coskewness pricing model implies that coskewness should be negatively related to alpha. Empirically, alpha and coskewness are of opposite signs for 67% of the funds under the static estimates and 61% for the time-varying estimates. The most common combination is a positive alpha estimate coupled with negative coskewness. Among the funds with positive alpha estimates, 83% have negative coskewness estimates. The same figure for funds with negative alpha estimates is only 50%. The correlation between alpha and coskewness estimates in the cross-section of funds is −32%.[10] Thus, the evidence supports the notion that seeking alpha may entail coskewness costs.

Table 2 presents regression coefficients of coskewness on alpha. It shows that there is a coskewness cost of alpha for funds: the regression coefficients are negative and significant. We also report the same regressions for standard stock portfolios to discern the extent of a trade-off in underlying securities. Panel A presents regressions in which coskewness and alpha are estimated

[10] When assessing the trade-off between alpha and coskewness, we winsorize the distributions of alpha and coskewness point estimates at the 1% and 99% levels to limit effects of outliers.

from the full time series. Panel B presents the time-series averages of daily cross-sectional regressions using the rolling window estimates of coskewness and alpha. In each panel, the first column presents results for mutual funds, and Columns 2–5 present results for four sets of characteristic-sorted portfolios described in the previous section. While the point estimates differ somewhat across different sets of assets and between static and time-varying estimates, they are all of the same order of magnitude. Thus, there is a trade-off between alpha and coskewness both among active mutual funds and among standard sets of stock portfolios. In Section 5, we use the stock portfolios to compute a price of coskewness and use that to compute alphas of mutual funds adjusted for coskewness.

2.2 Coskewness costs of active management

An active line of inquiry in the mutual fund literature is whether actions by managers reveal the existence of skilled asset management. The following fund activity measures have all been shown to predict mutual fund alphas:

- Industry concentration (Kacperczyk, Sialm, and Zheng 2005) measures the deviation of a fund's industry weights from market industry weights.
- Return gap (Kacperczyk, Sialm, and Zheng 2008) measures the deviation of a fund's realized return from those implied by its reported holdings.
- Active share (Cremers and Petajisto 2009) measures the deviation of a fund's portfolio weights from those of its stated benchmark.
- $1-R^2$ (Amihud and Goyenko 2013) uses the R^2 from an FFC monthly regression estimated over the previous 24 months to proxy for a fund's selectivity.
- Skill index (Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014) is a time-varying composite measure of market timing and stock picking where the weight on timing is the real-time recession indicator from Chauvet and Piger (2008).[11] Market timing and stock picking are measured by a fund's systematic or idiosyncratic performance relative to the market-weighted systematic or idiosyncratic performance, respectively.
- Active weight (Doshi, Elkamhi, and Simutin 2015) measures the deviation of a fund's portfolio weights from a value-weighted portfolio comprised of the fund's holdings.

We are interested in whether the various fund actions captured by these measures generate alpha at the expense of coskewness. The timing and horizons used to form portfolios varies across the papers that introduce these measures. We use a consistent portfolio formation rule across the measures. Specifically,

[11] In our sample period, Skill index predominantly sorts on stock picking, as the recession probability is less than one percent for 75% of the sample.

we sort funds into deciles each calendar quarter and form equal-weighted portfolios of funds. Following prior literature, the portfolios are based on the lagged activity measures. Table 3 reports the alphas and coskewness of the portfolios. The relationships between the activity measures and alphas are consistent with the prior literature. The estimated alphas of high-minus-low portfolios are both economically and statistically significant. However, across deciles of each activity measure, alpha and coskewness are negatively correlated. The trade-offs are highest for Active share, $1-R^2$, and Return gap. When we pool across activity measures, the coskewness per unit of alpha is worse than that for the cross-section of funds shown in Table 2. Furthermore, the high-minus-low portfolios all have negative point estimates of coskewness, and the coskewness is statistically significant in three of the six cases. For all strategies except Active weight, the coskewness estimate for the high-minus-low portfolio is worse than that of the median mutual fund.[12]

Among the decile portfolios formed from the activity measures, the trade-off between coskewness and alpha is largest for Active share, $1-R^2$, and Return gap and smallest for Skill index, Industry concentration, and Active weight. The alphas of these strategies could be due to market timing or security selection. Because market timing should generate a positive correlation between alpha and coskewness, the lower coskewness per unit of alpha for Active share, $1-R^2$, and Return gap indicates that they are the least related to market timing. Funds that rank highly by Active share, $1-R^2$, and Return gap seem to generate excess performance by stock selection, loading up on coskewness. On the other hand, Skill index, Industry concentration, and Active weight may all measure market timing to some extent. Of course, this is explicitly the case for the Skill index, which sorts on a weighted average of stock picking and market timing measures. Similarly, Doshi, Elkamhi, and Simutin (2015) show that approximately 13% of the alpha generated by Active weight is due to market timing (see their Table 6), and Jiang, Yao, and Yu (2007) find that market timing funds have high Industry concentrations. We present additional evidence that these measures are related to market timing in Section 3.4, where we relate coskewness to average activity measures in the cross-section of funds.

2.3 Styles

Previous research suggests that investment styles such as size, value, and momentum are related to coskewness (Harvey and Siddique 2000).[13]

[12] In Section 5.4, we adjust alphas directly for their coskewness cost. When performance is adjusted for coskewness in Table 11, the adjusted alphas are statistically insignificant in all but one case (Active weight).

[13] This is true in our sample. Table IA.1 in the Internet Appendix reports estimates of alpha and coskewness relative to the market for the FFC (Carhart 1997; Fama and French 1993) factors and a number of Russell and S&P benchmark indices related to size and value. SMB, HML, and UMD all have desirable alphas and undesirable coskewness during our sample period. The trade-off is the same for the indices: smaller capitalization indices have less desirable (more negative) coskewness than do larger cap indices, and value indices have less desirable coskewness than do growth indices. Among the 14 indices, the correlation between alpha and coskewness is −83%.

Table 3
Activity measures and performance

Decile	Industry concentration		Return gap		Active share		$1-R^2$		Skill index		Active weight	
	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\gamma}$
Lo	−0.44	−0.00	−0.14	−0.07	−0.61	0.00	−0.52	0.01	−0.22	−0.06	0.08	−0.12
2	−0.02	−0.07	0.12	−0.07	−0.48	0.00	−0.56	−0.01	−0.27	−0.08	0.17	−0.11
3	−0.01	−0.09	0.23	−0.05	−0.29	−0.00	−0.15	−0.04	−0.04	−0.11	0.33	−0.09
4	0.18	−0.08	0.29	−0.06	−0.31	−0.03	−0.22	−0.05	−0.01	−0.08	0.05	−0.07
5	0.26	−0.10	0.26	−0.07	0.14	−0.06	0.12	−0.08	0.01	−0.05	0.08	−0.05
6	0.40	−0.07	0.12	−0.06	0.39	−0.09	0.37	−0.10	0.07	−0.04	0.07	−0.06
7	0.31	−0.10	0.32	−0.07	0.78	−0.16	0.61	−0.12	0.17	−0.06	0.21	−0.05
8	0.65	−0.11	0.38	−0.08	1.35	−0.20	0.98	−0.12	0.47	−0.07	0.24	−0.05
9	0.95	−0.09	0.83	−0.12	1.33	−0.22	1.17	−0.17	1.08	−0.09	0.58	−0.07
Hi	0.73	−0.08	0.93	−0.16	1.68	−0.26	1.41	−0.20	1.80	−0.14	1.12	−0.13
Hi-lo	1.17**	−0.08*	1.07**	−0.09	2.29**	−0.26**	1.94***	−0.20***	2.02*	−0.08	1.04***	−0.01
t(Hi-lo)	(2.05)	(−1.89)	(2.01)	(−1.41)	(2.30)	(−2.35)	(3.43)	(−3.80)	(1.70)	(−1.10)	(3.21)	(−0.25)
Coef($\hat{\gamma}$, $\hat{\alpha}$)		−4.70		−8.92***		−11.80***		−9.17***		−2.95**		−4.36**
t(Coef)		(−1.70)		(−3.69)		(−21.53)		(−14.24)		(−2.73)		(−2.41)
Across activities												
Coef($\hat{\gamma}$, $\hat{\alpha}$)						−8.19***						
t(Coef)						(−8.65)						

Daily return series are formed by quarterly sorts of funds based on a given activity measure. Alpha and coskewness (γ) are estimated using each decile's resultant daily return series over the time period September 1, 1998 through June 30, 2014. The Active share decile time-series run from 1998 to 2009, because the Active share data obtained from Antti Petajisto's Web site are only available until 2009. $\hat{\alpha}$ is measured in basis points (*bps*) per day and coskewness $\hat{\gamma}$ is measured in $\%^3$ per day. Industry concentration (Kacperczyk, Sialm, and Zheng 2005) measures the deviation of a fund's industry weights from market-weighted industry weights. Return gap (Kacperczyk, Sialm, and Zheng 2008) measures the deviation of a fund's realized return from those implied by its reported holdings. Active share (Cremers and Petajisto 2009) measures the deviation of a fund's portfolio weights from those of its stated benchmark. $1-R^2$ (Amihud and Goyenko 2013) uses the R^2 from an FFC monthly regression estimated over the previous 24 months to proxy for a fund's selectivity. Skill index (Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014) is a time-varying composite measure of market timing and stock picking where the weight on timing is the real-time recession indicator from Chauvet and Piger (2008). Market timing and stock picking are measured by a fund's systematic or idiosyncratic performance relative to the market-weighted systematic or idiosyncratic performance, respectively. Active weight (Doshi, Elkamhi, and Simutin 2015) measures the deviation of a fund's portfolio weights from a value-weighted portfolio comprised of the fund's holdings. For each characteristic, the table reports the regression coefficient of coskewness (in $\%^3$ per day) on alpha (in % per day) like in Table 2. Statistical significance is represented by * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

Moreno and Rodríguez (2009) show their style classifications "Aggressive Growth," "Growth Income," and "Long-Term Growth" are related to the coskewness/alpha trade-off. Aggressive Growth has negative average coskewness and a positive CAPM alpha, whereas the other categories have positive coskewness and negative alphas. While styles matter, the alpha/coskewness trade-off in the cross-section of mutual funds is not entirely due to style choices. Table 4 reports mean alpha, mean coskewness, and the regression coefficient of coskewness on alpha for funds sorted into style bins. To construct the style bins, we use a holdings-based approach following Daniel et al. (1997) and Wermers (2003). Specifically, we classify each holding into one of five characteristic quintiles using the stock assignment file from Russ Wermer's Web site.[14] The characteristics we consider are size, book-to-market ratio, and momentum. To aggregate the holding-specific classification to the fund level, we first value-weight the quintile assignments for each reporting date. We then average across reporting dates to arrive at fund-specific average size, book-to-market, and momentum quintiles. We sort funds into terciles on each characteristic based on these averages. We intersect the size sort with the value sort (panel A), the size sort with the momentum sort (panel B), and the value sort with the momentum sort (panel C), creating nine bins in each case. The regression coefficient is negative in all bins and statistically significant at the 5% level in 25 of the 27 bins. Thus, there is a coskewness cost of alpha in funds even controlling for styles. An alternative way to control for styles is to consider loadings on style-based factors in addition to coskewness. Table IA.2 in the Internet Appendix shows that coskewness is negatively related to average fund returns even controlling for fund loadings on various style-based factors.

We account for the effects of styles on the trade-off in portfolios formed from sorts on activity measures in Internet Appendix A. Table IA.3 shows that there is a negative relation between coskewness and alpha when we pool across all the style-hedged portfolios. The majority of the Active share coskewness cost appears to come from coskewness embedded in its style exposures. The style-adjusted trade-off is largest for $1-R^2$ and Return gap. The stock selection activities of funds with these characteristics are costly from a coskewness perspective.

2.4 Trading

Table 5 reports regressions of coskewness on different components of alpha. We decompose alpha into three parts: the portion implied by a fund's time-series average holdings (static alpha), average expenses, and the remainder (dynamic alpha), which is due to trading. Coskewness is negatively related to both the static and dynamic components of alpha, so the trade-off does not merely reflect average holdings of stocks that bear a coskewness cost. The alpha/coskewness

[14] http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

Table 4
Trade-offs between alpha and coskewness within style bins

A. Size and value

	Small	Med	Large
Growth			
$\hat{\alpha}$ (bps)	0.52	−0.25	−1.27
$\hat{\gamma}$ ($\%^3$)	−0.20	0.00	0.08
Coef($\hat{\gamma}, \hat{\alpha}$)	−3.20	−1.28	−4.06
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−3.46	−2.29	−12.45
Neutral			
$\hat{\alpha}$ (bps)	0.75	−0.07	−0.55
$\hat{\gamma}$ ($\%^3$)	−0.21	−0.07	0.01
Coef($\hat{\gamma}, \hat{\alpha}$)	−4.84	−1.17	−2.33
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−4.89	−1.27	−2.56
Value			
$\hat{\alpha}$ (bps)	0.98	0.35	−0.12
$\hat{\gamma}$ ($\%^3$)	−0.23	−0.11	−0.03
Coef($\hat{\gamma}, \hat{\alpha}$)	−7.09	−3.00	−2.25
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−6.78	−2.76	−2.42

B. Size and momentum

	Small	Med	Large
Loser			
$\hat{\alpha}$ (bps)	0.70	0.24	−0.36
$\hat{\gamma}$ ($\%^3$)	−0.17	−0.08	0.00
Coef($\hat{\gamma}, \hat{\alpha}$)	−3.54	−2.14	−3.72
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−2.94	−2.52	−7.15
Average			
$\hat{\alpha}$ (bps)	1.04	0.05	−0.81
$\hat{\gamma}$ ($\%^3$)	−0.23	−0.07	0.02
Coef($\hat{\gamma}, \hat{\alpha}$)	−7.47	−0.73	−2.58
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−8.07	−0.70	−3.85
Winner			
$\hat{\alpha}$ (bps)	0.55	−0.15	−1.12
$\hat{\gamma}$ ($\%^3$)	−0.22	−0.06	0.05
Coef($\hat{\gamma}, \hat{\alpha}$)	−3.89	−2.61	−3.81
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−4.71	−2.98	−7.01

C. Value and momentum

	Growth	Neutral	Value
Loser			
$\hat{\alpha}$ (bps)	−0.85	−0.18	0.29
$\hat{\gamma}$ ($\%^3$)	0.06	−0.03	−0.09
Coef($\hat{\gamma}, \hat{\alpha}$)	−2.84	−2.81	−3.25
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−3.88	−3.85	−3.75
Average			
$\hat{\alpha}$ (bps)	−0.61	0.04	0.55
$\hat{\gamma}$ ($\%^3$)	0.01	−0.08	−0.16
Coef($\hat{\gamma}, \hat{\alpha}$)	−2.76	−3.06	−6.35
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−5.06	−3.02	−5.97
Winner			
$\hat{\alpha}$ (bps)	−0.06	0.18	0.50
$\hat{\gamma}$ ($\%^3$)	−0.10	−0.15	−0.23
Coef($\hat{\gamma}, \hat{\alpha}$)	−3.24	−3.37	−5.74
t(Coef($\hat{\gamma}, \hat{\alpha}$))	−5.41	−3.42	−2.48

Alpha and coskewness (γ) are estimated for active mutual funds over the time period September 1, 1998 through June 30, 2014, using daily returns and winsorized at the 1% and 99% levels. Alpha is measured in basis points (bps) per day and coskewness (γ) is measured in $\%^3$ per day. Style classifications are based on funds' holdings. At each reporting date, we assign each stock to size, book-to-market, and momentum quintiles based on Russ Wermer's stock assignment file. For each characteristic and each fund, we value weight the rankings and average across reporting dates. We sort funds into terciles on each characteristic and intersect the sorts. The top two entries in each cell report the average alpha and coskewness. The bottom two entries in each cell report the regression coefficient and associated t-statistics of coskewness (in $\%^3$ per day) regressed on alpha (in % per day) like in Table 2.

Table 5
Coskewness costs of static and dynamic alphas

	(1) $\hat{\gamma}$	(2) $\hat{\gamma}$	(3) $\hat{\gamma}$	(4) $\hat{\gamma}$
$\hat{\alpha}$	−3.39***		−0.98***	
	(−12.38)		(−3.36)	
Static $\hat{\alpha}$		−4.00***		−1.08***
		(−13.81)		(−3.22)
Dynamic $\hat{\alpha}$		−3.35***		−1.07***
		(−12.12)		(−3.53)
Expenses		−11.78***		−3.68**
		(−5.59)		(−1.98)
Constant	−0.09***	0.02		
	(−28.75)	(1.63)		
Adjusted R^2	0.099	0.133	0.383	0.384
Style controls	No	No	Yes	Yes

The table reports cross-sectional regressions of coskewness on alpha and components of alpha. Alpha and coskewness (γ) are estimated for active mutual funds and their holdings over the time period September 1, 1998 through June 30, 2014, using daily returns and winsorized at the 1/99% level. $\hat{\alpha}$ is measured in % per day and coskewness $\hat{\gamma}$ is measured in $\%^3$ per day. Alpha for active funds is decomposed into the alpha implied by a fund's time-series average holdings (static alpha), average expenses, and the remainder (dynamic alpha) like in Equation (7). Static $\hat{\alpha}_i$ is $\sum_{j=1}^{N_i} \bar{\omega}^i_j \hat{\alpha}_j$ where $\bar{\omega}^i_j$ denotes the time-series average holding of stock j by fund i, $\hat{\alpha}_j$ is the estimated alpha for stock j, and N_i is the number of stocks reported held by the fund. Dynamic $\hat{\alpha}$ is the fund's estimated alpha minus the static alpha net of expenses. We report regressions with and without style fixed effects. Style classifications are based on funds' holdings. At each reporting date, we assign each stock to size, book-to-market, and momentum quintiles based on Russ Wermer's stock assignment file. For each characteristic and each fund, we value weight the rankings and average across reporting dates. We sort funds into terciles on each characteristic and intersect the sorts. We include dummy variables in the regression for each of the 27 classifications. t statistics are in parentheses, and statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

trade-off is also due to funds' trading decisions. These trading decisions could result in time-varying risk exposures that would affect dynamic alpha (see Section 3.1). Trading could also reflect dynamic security selection by fund managers (see Section 3.4).

The specific decomposition is

$$\hat{\alpha}^i = \underbrace{\sum_{j=1}^{N_i} \bar{\omega}^i_j \hat{\alpha}_j}_{\text{Static Alpha}} - \underbrace{\frac{1}{T_i}\sum_{t=1}^{T_i} \text{Exp}^i_t}_{\text{Average Expenses}} + \underbrace{\left[\hat{\alpha}^i - \left(\sum_{j=1}^{N_i} \bar{\omega}^i_j \hat{\alpha}_j - \frac{1}{T_i}\sum_{t=1}^{T_i} \text{Exp}^i_t\right)\right]}_{\text{Dynamic Alpha}}, \quad (7)$$

where N_i is the number of stocks reported held by fund i at any point over the sample, T_i denotes the number of daily return observations for fund i, ω^i_{jt} is the holding weight of asset j for fund i as of the most recent disclosure date, and $\bar{\omega}^i_j = \frac{1}{T_i}\sum_{t=1}^{T_i} \omega^i_{jt}$ is the time-series average holding weight.[15] Average expenses equal the annual expense ratio divided by 252. For each underlying asset j, we

15 Note that this decomposition is not perfect due to discreteness in the timing of fund holdings disclosures. For example, a portion of the alpha due to a buy-and-hold position entered into just after a reporting date will be assigned to dynamic alpha, while the same buy-and-hold position entered into on the reporting date will largely be contained in the static alpha. Nonetheless, the decomposition is useful for disentangling whether the trade-off between coskewness and alpha is purely a function of the trade-off in stocks.

estimate α_j over the same time period used to estimate fund i's alpha. Dynamic alpha is thus the fund's estimated alpha minus the static alpha and expenses. Note that dynamic alpha is net of trading costs, which we do not observe.

Column 2 of Table 5 reports the regression of coskewness on the components of alpha without style controls, and Column 4 reports the regression including dummy variables for the 27 styles formed by intersecting the size, book-to-market, and momentum terciles. With or without style controls, there is a significant trade-off between coskewness and each component of alpha. The results show that the negative relation between alpha and coskewness is due both to average fund composition (static alpha) and other fund choices (dynamic alpha). Coskewness is also lower for funds with higher expenses, suggesting that more active management results in less desirable coskewness in funds.[16]

3. Determinants of Coskewness in Mutual Funds

As discussed in the Introduction, there are at least three possible sources of coskewness in fund returns that are distinct from the coskewness of stocks held by funds: market timing, cash management, and derivatives.

3.1 Time-varying market exposures

Ferson and Schadt (1996) argue that mutual funds should be evaluated by conditional alphas and propose a model of time-varying factor exposures. They also point out that time-varying market exposures can create convexity or concavity (coskewness) relative to the market return. To determine the amount of coskewness that is due to time-varying market exposures, we run the following regression:

$$R_{it}-R_{ft}=a_i+b_{i1}(z_{t-1})(R_{mt}-R_{ft})+u_{it}, \tag{8}$$

where $b_{i1}(z_{t-1})=b_{i0}+\mathbf{b}_i' z_{t-1}$ and z_{t-1} is a vector of deviations of the public conditioning variables from their unconditional means. We then calculate the coskewness of the excess return a_i+u_{it} relative to the market return, which we denote by γ_i^{NTVB}.[17] This is the coskewness of the fund *n*ot due to *t*ime-*v*arying

Holdings are also not observed perfectly. For instance, short positions are not disclosed. We adjust weights each disclosure period for the percent of assets held in common stocks, cash, bonds, etc reported in CRSP. These broad asset class percentages are missing in CRSP for many funds in the early part of our sample. For funds with nonmissing data at some point in the sample period, we assign their time-series average weight to these missing periods. For the few funds with no nonmissing asset-class breakdowns, we assign the unconditional sample average weights. For the noncommon stock holdings, we assign cash and other securities the Treasury-bill rate, while bonds, preferred stock, and other securities are assigned the Lehman/Barclays Aggregate Bond Index total return, like in Kacperczyk, Sialm, and Zheng (2008). Finally, other equity is assigned the CRSP value-weighted stock return.

16 This is borne out in the analysis in Section 3.4, which shows that other measures related to active management like turnover are negatively related to coskewness.

17 Alternatively, we could run the regression

$$R_{it}-R_{ft}=\tilde{a}_i+\tilde{b}_{i1}(z_{t-1})(R_{mt}-R_{ft})+\tilde{b}_{i2}(R_{mt}-R_{ft})^2+\eta_{it}.$$

*b*etas based on the public information. It may contain market timing activities based on private information as well as other actions affecting coskewness. The component of coskewness γ that is due to *t*ime-*v*arying *b*etas is $\gamma^{\text{TVB}} = \gamma - \gamma^{\text{NTVB}}$. Like in Ferson and Schadt (1996), the conditioning vector consists of the dividend yield of NYSE/AMEX firms over the previous 12 months, the 1-month Treasury-bill yield, the term spread (10-year Treasury less 3-month Treasury yields), and the default spread (Baa minus Aaa corporate yields).[18]

As discussed before, good market timers create positive alphas and positive coskewness, and bad market timers create negative alphas and negative coskewness, so we expect the relation between alpha and coskewness due to time-varying betas to be positive. Table 6 shows that this is indeed the case: γ^{TVB} is positively related to alphas. This means that the undesirable coskewness per unit of alpha is even higher for the component of fund returns not due to public information market timing than it is for total fund returns. This is also shown in Table 6. The negative correlation between γ^{NTVB} and alpha implies that any market timing ability based on private managerial signals (which would result in a positive correlation) is dominated by alpha-generating activities that create negative coskewness.

If the average fund is a good market timer based on public information, then we should find less convexity on average in the residuals (that is, lower coskewness) when we account for market timing via time-varying betas. The reverse would be true if the average fund is a bad market timer based on public information. In the 67 funds analyzed by Ferson and Schadt (1996) using monthly data, average coskewness went from negative to zero when time-variation in betas was allowed, which is consistent with the time-varying betas based on public information being negative market timing. In our sample, likewise, daily average coskewness increases when time variation in betas is allowed. The t-statistic of the difference $\gamma^{\text{NTVB}} - \gamma$ is 3.1. However, the economic magnitude of the difference is small (it equals $0.0047\%^3$, which is only 3% of the cross-sectional standard deviation of γ), and the average γ^{NTVB} is significantly negative.

Ferson and Schadt (1996) observe that the time-varying betas they estimate are related to flows. Further evidence on this point is provided by Ferson and Warther (1996). Edelen (1999) also shows that flow-induced trading harms performance. Motivated by this, we add lagged fund flows (demeaned by the fund-specific mean) to the Ferson-Schadt conditioning variables: panel B of Table 6 presents the results from the augmented model. When we control for styles, γ^{TVB} is again positively and significantly related to alpha. Moreover,

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This is the regression of Ferson and Schadt (1996) and Ferson and Warther (1996). In parallel with the discussion of Section 1.2, the coefficient $\tilde{b}_{i2}$ is a positive multiple of the coskewness of the excess return $a_i + u_{it}$ in (8), and the constant of proportionality depends only on market moments.

18 We obtain dividend yields from CRSP and other conditioning variables from the Federal Reserve Economic Data (FRED). Following Barras, Scaillet, and Wermers (2010), we omit the January dummy included by Ferson and Schadt (1996) in the set of conditioning variables. Our results are unaffected by its inclusion.

Table 6
Coskewness and time-varying betas

A. Time-varying betas conditional on public information

	$\hat{\gamma}$	$\hat{\gamma}^{\text{NTVB}}$	$\hat{\gamma}^{\text{TVB}}$	$\hat{\gamma}$	$\hat{\gamma}^{\text{NTVB}}$	$\hat{\gamma}^{\text{TVB}}$
$\hat{\alpha}$	−3.388***	−4.088***	0.683***	−0.981***	−1.615***	0.606***
	(−12.38)	(−14.15)	(5.24)	(−3.36)	(−5.42)	(4.02)
Constant	−0.086***	−0.081***	−0.004***			
	(−28.75)	(−25.73)	(−3.02)			
Adj. R^2	0.099	0.125	0.019	0.383	0.386	0.245
Style	No	No	No	Yes	Yes	Yes

B. Time-varying betas conditional on public information and flows

	$\hat{\gamma}$	$\hat{\gamma}^{\text{NTVB}}$	$\hat{\gamma}^{\text{TVB}}$	$\hat{\gamma}$	$\hat{\gamma}^{\text{NTVB}}$	$\hat{\gamma}^{\text{TVB}}$
$\hat{\alpha}$	−3.388***	−3.263***	−0.092	−0.981***	−1.276***	0.290**
	(−12.38)	(−12.46)	(−0.76)	(−3.36)	(−4.41)	(2.02)
Constant	−0.086***	−0.069***	−0.016***			
	(−28.75)	(−24.84)	(−13.56)			
Adj. R^2	0.099	0.106	0.000	0.383	0.325	0.063
Style	No	No	No	Yes	Yes	Yes

Following Ferson and Schadt (1996), we allow for time-varying betas conditional on public information. γ_i^{NTVB} is the coskewness of $a_i + u_{it}$ with the market return where $a_i + u_{it}$ is the excess return from Equation (8):

$$R_{it} - R_{ft} = a_i + b_{i1}(z_{t-1})(R_{mt} - R_{ft}) + u_{it}.$$

$b_{i1}(z_{t-1}) = b_{i0} + \mathbf{b}_i' z_{t-1}$ and z_{t-1} is a vector of deviations of the public conditioning variables from their unconditional means. The conditioning vector includes the dividend yield of NYSE/AMEX firms over the previous 12 months, the 1-month Treasury-bill yield, the term spread (10-year Treasury less 3-month Treasury yields), and the default spread (Baa minus Aaa corporate yields). Panel A reports cross-sectional regressions of the market-model coskewness (γ_i), coskewness of the fund *n*ot due to *t*ime-*v*arying *b*etas based on the public information (γ_i^{NTVB}), and the coskewness due to *t*ime-*v*ariation in *b*etas associated with public information ($\gamma_i^{\text{TVB}} = \gamma_i - \gamma_i^{\text{NTVB}}$). In the spirit of Edelen (1999) and Ferson and Warther (1996), we augment the model to allow market exposures to vary due to daily net fund flows. Specifically, we include demeaned fund-specific flows in the vector of conditioning variables. These results are presented in panel B. Regressions with and without style fixed effects, as described in previous tables, are reported. t statistics are in parentheses, and statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

alpha is negatively correlated with the component of coskewness that is not due to betas varying based on either public macro information or fund-specific flows.

3.2 Cash management

Mutual funds are financial intermediaries that receive money from and distribute money to investors, who compensate funds to invest on their behalf. Coskewness and alpha may be affected by the liquidity services provided by mutual funds to investors (Edelen 1999). For instance, it is more costly for managers to deploy cash inflows into illiquid investments, and it is also more costly to liquidate illiquid positions to satisfy investor outflows. In this section, we show that liquidity management is also related to coskewness.

For each fund, we calculate two measures designed to capture variation in liquidity provision costs across funds. First, we calculate the average illiquidity measure of Amihud (2002) for the fund's underlying holdings. Specifically, we calculate a stock's average Amihud measure each quarter and aggregate to

Table 7
Coskewness and liquidity management

	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$
$\hat{\alpha}$	−2.990***	−3.010***	−0.891***	−0.911***
	(−10.96)	(−10.95)	(−3.06)	(−3.12)
Hold. illiquidity	−0.037***	−0.038***	−0.018***	−0.019***
	(−7.85)	(−8.71)	(−4.33)	(−4.78)
Abnormal cash		−0.004		−0.003
		(−1.01)		(−0.90)
Hold. illiquidity × Abnormal cash		0.009***		0.008***
		(3.01)		(3.42)
Adjusted R^2	0.145	0.151	0.392	0.396
Style	No	No	Yes	Yes

The table reports analysis of the relation between coskewness and variables related to liquidity management. Coskewness (γ) and alpha are estimated for active funds over the time period September 1, 1998 through June 30, 2014, using daily returns. Each quarter, we calculate a stock's average Amihud measure each quarter and aggregate to the fund-quarter level using a fund's holding weights. Holdings illiquidity for a given fund is the time-series average of these fund-quarter Amihud measures. Abnormal Cash is the residual from a cross-sectional regression of funds' average cash holdings as a fraction of TNA on fund characteristics. The fund characteristics include fund size (TNA), age, management fees, expense ratio, 12b-1 fees, family TNA, and dummy variables for the fund's style classification as described in Table 5. Holdings Illiquidity and Abnormal Cash are scaled by their respective cross-sectional standard deviations.

the fund-quarter level using the fund's holding weights. For each fund, we use the time-series average of these fund-quarter Amihud measures to capture the average costs faced by managers needing to invest new cash or to liquidate positions to satisfy investor withdrawals. Second, motivated by Simutin (2014), we calculate the abnormal cash balances for each fund. Abnormal cash is the residual from a cross-sectional regression of cash as a fraction of TNA on fund characteristics (fund size, age, management fees, expense ratio, 12b-1 fees, family TNA, and dummy variables for the fund's style classification as described in Table 5). Funds may keep extra cash in order to help satisfy investor withdrawals or they may keep cash to preserve flexibility for time-varying investment opportunities.

We find strong evidence of lower coskewness for funds with less liquid holdings. However, this effect is mitigated when firms have abnormally high levels of cash. Thus, illiquidity of holdings in conjunction with low levels of cash induce negative market timing in the sense of lower coskewness (greater concavity with respect to the market return). Table 7 presents cross-sectional regressions of fund coskewness on alpha and the two liquidity measures and their interaction. Without style controls, funds with one-standard deviation more illiquid holdings have $0.04\%^3$ lower coskewness, which is about one-quarter of the cross-sectional standard deviation of coskewness. Column 2 shows that this effect is lessened slightly for funds with higher abnormal cash holdings. A large portion of the negative coskewness effects of holdings illiquidity are related to styles. Controlling for styles, funds with one-standard deviation more illiquid holdings have $0.02\%^3$ lower coskewness, which is about 11% of the cross-sectional standard deviation of coskewness (Column 3). The detrimental effect of illiquid holdings is partially offset by holding more cash after controlling for styles (Column 4). The point estimate indicates that the relationship between coskewness and holdings illiquidity is almost halved for a fund with a one-standard-deviation larger abnormal average cash balance. Thus, funds with illiquid holdings and low levels of abnormal cash exhibit lower coskewness, consistent with potential coskewness costs associated with cash management.[19] In all of the specifications, there continues to be a negative relation between coskewness and alpha when we control for cash management.

3.3 Derivatives

Derivatives can create a return profile that is convex or concave in the market return, implying positive or negative coskewness. Under the assumptions of Jagannathan and Korajczyk (1986) or Leland (1999), the coskewness created by derivatives is negatively related to alphas. We explore the coskewness created by derivatives by collecting NSAR filings for funds in our sample from the SEC Web site.[20] Funds are required to disclose various activities in their NSAR filings. In particular, they must disclose whether they are allowed to invest in certain derivative products as well as whether they actually engaged in such activity over the six-month reporting period. We are particularly interested in activity associated with options on equities, options on stock indices, stock index futures, and options on stock index futures, as these derivatives can be used to create convexity or concavity in fund returns. For instance, selling covered calls can generate revenue at the expense of coskewness. Similarly, purchasing portfolio insurance can create positive coskewness.

Earlier work in the market timing literature dismissed derivatives as a source of coskewness, arguing that mutual funds do not use derivatives. For instance, Connor and Korajczyk (1991) ruled out derivative use through an examination of fund prospectuses. Of course, the investment environment and derivatives markets have changed significantly over the last 25 years. In particular, the Taxpayer Relief Act of 1997 repealed the "short-short rule," which limited the use of derivatives by mutual funds.[21] Most funds in our sample are allowed

[19] Simutin (2014) finds that a higher level of abnormal cash is weakly associated with better market timing measures. The evidence we find on this association is also weak and somewhat inconsistent. In untabulated univariate regressions, we obtain the same sign as Simutin: coskewness is positively related to abnormal cash (but the coefficient is insignificant). However, in Table 7, with controls for alpha and holdings illiquidity, the coefficient is negative (again insignificant).

[20] Funds file NSAR forms semiannually. We collect all NSAR forms filed with the SEC from 1998 to 2014. For each fund in the sample, we match by fund name to the latest NSAR filed in the final year the fund appears in our sample. We initially match using a computer algorithm (bigram string matching) and then match by hand. When multiple funds appear in the same filing, we match the fund name using question 7 from the NSAR. If no NSAR form exists for the final year the fund appears, we match to the latest NSAR form in the prior calendar year. We augment the hand-matched sample with prior year filings using bigram string matching, and take an average of responses over all matched periods. We match 2,919 of 3,001 funds in the sample to at least one filing.

[21] Under the "short-short rule," funds could not collect more than 30% of revenues from securities held fewer than 3 months in order to be considered "pass-through" entities. Bae and Yi (2008) find evidence that the "perverse" market timing of funds was reduced after this repeal. They report that aggregate derivative use increased in funds following the rule change, but they do not relate derivative use to changes in market timing directly. They also do not consider the possible trade-off between coskewness created using derivatives and alpha.

Table 8
Coskewness, alpha, derivatives and other disclosed activities

A. Prevalence of derivatives use and other activities

Activity	Proportion
Writing or investing in options on equities	0.227
Writing or investing in options on stock indices	0.093
Writing or investing in stock index futures	0.279
Writing or investing in options on stock index futures	0.032
Writing or investing in other commodity futures	0.022
Investments in shares of other investment companies	0.809

B. Regressions of coskewness and alpha on disclosed activities

	$\hat{\gamma}$	$\hat{\alpha}$
Writing or investing in options on equities	−0.17*	−0.03
	(−1.75)	(−0.32)
Writing or investing in options on stock indices	0.39**	−0.24*
	(2.55)	(−1.75)
Writing or investing in stock index futures	0.05	−0.25***
	(0.84)	(−4.81)
Writing or investing in options on stock index futures	0.75***	−0.20
	(3.64)	(−0.76)
Writing or investing in other commodity futures	−0.72*	0.29
	(−1.82)	(0.76)
Investments in shares of other investment companies	−0.13***	0.25***
	(−2.71)	(5.16)
Constant	−0.37***	−0.29***
	(−7.27)	(−5.26)
R^2	0.013	0.046

The table reports analysis of the relation between coskewness and alpha with funds' SEC disclosed activities. Coskewness (γ) and alpha are estimated for active funds over the time period September 1, 1998 through June 30, 2014, using daily returns. Disclosed activities are reported in question 70 of each fund's NSAR form. Panel A presents the summary statistics of whether a fund participated in the indicated activity in at least one of the matched semiannual reporting periods. We tabulate the complete list of disclosed activities in panel A of Table IA.4. Panel B presents estimates from a regression of coskewness (Column 1) and alpha (Column 2) on each fund's average response across all matched NSAR periods, where in each period a 1 indicates the fund engaged in the activity and 0 indicates it did not. In panel B, we control for all activities disclosed in the NSAR, but only report those related to our empirical predictions. We report the coefficient estimates on all additional activities in panel B of Table IA.4.

to invest in derivatives, consistent with earlier evidence on constraints in Deli and Varma (2002) and Almazan et al. (2004). In our sample, 94% of funds are allowed to invest in options on equities, 92% in options on stock indices, 89% in stock index futures, and 88% in options on stock index futures. Thus, for most funds, the extent to which funds employ derivatives is an investment choice for fund managers.

Table 8 reports how many funds use derivatives (panel A) and their relation with coskewness and alpha (panel B). We find that a nontrivial fraction of funds actually do utilize derivatives, consistent with evidence in Koski and Pontiff (1999), Cici and Palacios (2015), and Natter et al. (2016). 22.7% of funds report the use of equity options at least once, and these funds exhibit significantly lower coskewness (more concavity with the market). This is consistent with fund managers selling covered calls on positions. Some funds (9.3%) report usage of options on stock indices. These funds have significantly higher coskewness (less concavity or more convexity with the market), but also lower alpha.

This is consistent with funds purchasing market puts as portfolio insurance.[22] Some funds (27.9%) report the use of stock index futures. These funds have higher coskewness point estimates (although not statistically significant) and significantly lower alphas. This is consistent with funds using stock index futures to create synthetic puts.[23] Some funds (3.2%) invest in options on stock index futures. These funds have higher coskewness and lower alpha, consistent with the use of options on futures to create portfolio insurance. Thus, there is evidence that some managers are employing derivative strategies to shape their return distributions relative to the market. We find similar results controlling for fund styles (tabulated in Table IA.4 of the Internet Appendix). Funds employing these strategies are still a minority of the sample. In total, 24% of the funds report using at least one of equity options, equity index options, or options on equity index futures in some reporting period.[24]

Aside from derivatives, several other disclosed activities are strongly related to both coskewness and alpha. Investments in restricted securities, which are generally less liquid securities, are made in at least one reporting period by 38% of the funds in the sample, and they are associated with lower coskewness and higher alphas. Similarly, investments in shares of other investment companies (which are used by four-fifths of the funds in the sample) are also associated with lower coskewness and higher alphas.

3.4 The relative importance of different fund activities for coskewness

In this section, we determine which activities are the most important drivers of funds' coskewness. Columns 1–3 of Table 9 report estimates of the amount of variation in coskewness explained by each fund characteristic. The table presents the partial sum of squares associated with each characteristic normalized by the total of all partial sums of squares. Therefore, the total of each column sums to one, and each characteristic's value can be interpreted as the proportion of explained variation. Columns 4 and 5 report the regression coefficients from the ANOVA models presented in

[22] The interpretation that individual equity options are predominantly covered calls and that index options are predominantly protective put positions is consistent with the evidence in Cici and Palacios (2015). Using holdings data on options by funds, they show that the majority of equity option positions are written calls and that the majority of index option positions are long puts.

[23] Frino, Lepone, and Wong (2009) show that the use of futures to quickly gain market exposure and avoid cash drag improves both market timing and abnormal return performance in a sample of Australian funds. The lower alphas found in our sample suggest this cash-equitization channel is not the predominant use of futures in our sample.

[24] In their survey of mutual funds, Koski and Pontiff (1999) found that 21% of funds use derivative securities. They test whether derivative use is related to the market timing measure of Henriksson and Merton (1981), which is an alternative to the quadratic model (5) and is thus related to coskewness. They conclude that derivative use is generally unrelated to various risk measures including the market timing beta. However, as shown in Table 8, different strategies using options and futures can result in both more convexity or more concavity. Pooling various derivatives may therefore mask results. Cici and Palacios (2015) do not run market timing regressions. The focus of Natter et al. (2016) is the abnormal returns of options users versus nonusers. In robustness tests, they report using both unconditional and conditional market timing specifications, but do not report the associated coskewness estimates.

Table 9
Determinants of coskewness

	ANOVA			Regression	
	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}$
Fund activities					
Market timing		0.004	0.035	0.039	0.087***
				(1.13)	(2.82)
Stock picking		0.011	0.000	−0.066**	−0.006
				(−1.98)	(−0.19)
Active share		0.544	0.095	−0.545***	−0.233***
				(−12.75)	(−5.21)
Return gap		0.001	0.002	−0.014	−0.020
				(−0.54)	(−0.77)
Industry concentration		0.060	0.083	0.160***	0.148***
				(5.74)	(5.38)
$1-R^2$		0.002	0.001	−0.033	−0.016
				(−0.86)	(−0.42)
Active weight		0.064	0.033	0.149***	0.092***
				(6.77)	(3.82)
Dispersion		0.000	0.002	0.005	−0.022
				(0.25)	(−1.09)
Turnover		0.043	0.054	−0.122***	−0.110***
				(−4.51)	(−3.97)
Tracking error		0.001	0.000	0.022	0.008
				(0.48)	(0.18)
NSAR activities		0.028	0.052		
Investor effects					
Holdings illiquidity		0.078	0.061	−0.161***	−0.112***
				(−5.91)	(−3.87)
Abnormal cash		0.000	0.004	0.001	−0.029
				(0.05)	(−1.18)
Hold. illiquidity× Abn. cash		0.007	0.001	−0.047*	−0.016
				(−1.95)	(−0.64)
Fund characteristics					
Number of stocks		0.149	0.017	−0.253***	−0.077***
				(−9.98)	(−3.27)
TNA		0.002	0.000	0.030*	0.005
				(1.89)	(0.37)
Expense ratio		0.000	0.001	0.012	0.016
				(0.52)	(0.74)
Family TNA		0.004	0.000	−0.039***	−0.005
				(−2.76)	(−0.39)
Asset allocation					
Size effect	0.806		0.333		
Value effect	0.161		0.219		
Momentum effect	0.033		0.008		
Adj. R^2	0.36	0.39	0.48	0.39	0.48
Style controls	Yes	No	Yes	No	Yes
NSAR controls	No	Yes	Yes	Yes	Yes
Standardized coef.	N/A	N/A	N/A	Yes	Yes

Columns 1–3 report analysis of variance of coskewness. Each column reports the partial sum of squares of each characteristic scaled by the total partial sum of squares for all included characteristics. Columns 4 and 5 report standardized coefficients from the regressions corresponding to Columns 2 and 3. Coskewness (γ) is estimated for active funds using daily returns from September 1, 1998 through June 30, 2014. TNA is the average total net assets of the fund. Expense ratio is the average expense ratio for each fund from CRSP. Turnover is the average fund turnover from CRSP. Active share and tracking error are the averages taken through 2009 as reported in the data from Antti Petajisto. Industry concentration, Active weight, Return gap, and $1-R^2$ are defined like in Table 3. Market timing, Stock picking, and Dispersion are calculated like in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). As described in Table 7, Holdings Illiquidity is the the weighted average Amihud measure of each fund's underlying holdings, and Abnormal Cash is the residual from a cross-sectional regression of funds' average cash holdings as a fraction of TNA on fund characteristics. NSAR Activities are a set of fund time-series averages of 18 dummy variables equal to 1 if the fund engaged in the activities described in Table 8 in a given semiannual period. The variation explained by these variables is aggregated in Columns 2 and 3. Columns 4 and 5 include NSAR variables (coefficients omitted for space). Style controls are formed like in Table 5. N/A refers to not applicable.

Columns 2 and 3, respectively. Column 1 includes only dummy variables for the fund's style classification across size, value, and momentum terciles. Column 2 includes fund characteristics related to the funds' activities, the effects of liquidity management issues related to managing investor flows, and other characteristics. Specifically, the specification includes each fund's time-series average characteristic for the activities in Table 3. We decompose the skill index into stock picking and market timing following Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), and we also include their measure of holdings dispersion. Dispersion is related to herding by fund managers. In addition, fund turnover and tracking error are included along with indicator variables for each of the NSAR activities described in Table 8. Finally, the three measures of liquidity provision costs from Table 7 are included. Other characteristics are TNA (fund and family), number of holdings, and expense ratio. Column 3 adds style fixed effects to these fund characteristics.

Column 1 of Table 9 shows that style fixed effects explain 36% of the cross-sectional variation in coskewness. This is driven largely by the size characteristic, which accounts for 80% of the variation explained by styles. In Column 2, characteristics alone explain slightly more variation (R^2 of 39%). The characteristic that explains the most variation in coskewness is the fund's Active share, accounting for roughly 50% of the explained variation. The corresponding regression coefficient in Column 4 shows that this is strongly negatively related to coskewness.

Active weight and Industry concentration are the next most important characteristics associated with coskewness. Interestingly, while these activity measures show a strong alpha/coskewness trade-off in the portfolio sorts in Table 3, they are positively related to coskewness when we control for other characteristics. As discussed in Section 2.2, these activity measures may capture both market-timing and stock selection (Ferson and Mo 2016). In particular, Doshi, Elkamhi, and Simutin (2015) find that approximately 13% of the alpha generated by Active weight is related to market timing. Jiang, Yao, and Yu (2007) show that market timing funds have high levels of Industry concentration. It is therefore not surprising that, after controlling for a variety of activities, some are positively related to coskewness. Consistent with the trade-off in Table 3, the other measures associated with active management are important and generally negatively related to coskewness. For example, turnover and NSAR activities each explain an economically important amount of the variation in coskewness.

Column 3 includes both style controls and characteristics. The R^2 in this specification is substantially higher (R^2 of 48%) than in Column 1, providing further evidence that characteristics beyond styles explain a substantial amount of variation. In general, the results are consistent with those in Column 2. Although it remains the most important activity, Active share accounts for substantially less of the explained variation after controlling for styles. Active share and turnover, which both capture dynamic selection activities to some degree, contribute negatively to coskewness, accounting for 15% of the explained variation in coskewness. After including other controls, Market timing is positively related to coskewness as expected. Market timing, Active weight, and Industry concentration, all of which seem to be related to market timing activity, collectively account for 15% of the explained variation in coskewness. Variables related to cash management (illiquidity of holdings and abnormal cash holdings) explain an additional 7%. Derivatives usage and other disclosed activities account for 5% of the explained variation in coskewness. Overall, the results are consistent with more active funds bearing a larger coskewness cost, but certain characteristics, in particular those that either directly measure market timing or are partly due to market timing, such as Industry concentration and Active weight, are actually associated with better coskewness.

Table IA.5 in the Internet Appendix reports the same analysis for coskewness that is not due to time varying betas (γ^{NTVB} from subsection 3.1). The results for this measure are similar with two notable exceptions. First, while market timing is positively and significantly related to overall coskewness, this appears to be primarily due to timing based on public information (time-varying betas) rather than timing based on private information. Second, part of the negative association of higher turnover funds with lower coskewness is due to time-varying betas. Thus, more active management (turnover) results in time-varying market exposures that are correlated with public information.

4. Why Coskewness Is Important to Fund Managers: Flows

It is well known that mutual fund flows respond to fund performance as measured by alpha (see, for example, Sirri and Tufano (1998), Berk and van Binsbergen (2016), Barber, Huang, and Odean (2016)). This section shows that money also flows to funds that have desirable coskewness. We augment flow-performance regressions of new money growth on alpha to include coskewness. We measure monthly new money growth (NMG_{t+1}) for each fund as

$$\frac{\mathrm{TNA}_{i,t+1}-\mathrm{TNA}_{i,t}(1+R_{i,t+1})}{\mathrm{TNA}_{i,t}(1+R_{i,t+1})}\times 100, \tag{9}$$

where $\mathrm{TNA}_{i,t}$ is the total net assets of fund i in month t and $R_{i,t+1}$ is the return of fund i from month t to $t+1$. We calculate time-varying estimates of alpha and coskewness measured over the 5-year period ending at the end of the prior month. Panel A of Table 10 reports average new money growth within 5×5 sorts of alpha and coskewness. For each alpha quintile, the difference in flows between the high and low coskewness quintiles is positive. This suggests that investor flows are related to coskewness.

Panel B of Table 10 reports regressions of new money growth on the lagged estimates of alpha and coskewness. The independent variables alpha

Table 10
Sensitivity of flows to alpha and coskewness

A. Flow–performance sorts

	$\hat{\alpha}_t$ Quintiles					
$\hat{\gamma}_t$ Quintiles	Lo	2	3	4	Hi	Hi-lo
Lo	−1.69	−1.25	−0.85	−0.18	0.86	2.55***
2	−1.52	−1.07	−0.65	−0.05	1.12	2.64***
3	−1.42	−0.77	−0.46	0.27	1.29	2.71***
4	−1.34	−0.62	−0.16	0.65	1.49	2.83***
Hi	−1.31	−0.70	−0.13	0.51	1.44	2.75***
Hi-lo	0.38**	0.55***	0.72***	0.69***	0.58**	

B. Flow–performance regressions

	NMG_{t+1}	NMG_{t+1}	NMG_{t+1}
$\hat{\alpha}_t$	0.99***	1.02***	0.91***
	(20.43)	(21.86)	(16.38)
$\hat{\gamma}_t$		0.17***	0.12***
		(4.78)	(2.67)
$\hat{\alpha}_t \times$ Inst fund			0.24***
			(3.76)
$\hat{\gamma}_t \times$ Inst fund			0.10*
			(1.83)
Institutional fund			−0.13**
			(−2.23)
ln(TNA)	−0.19***	−0.20***	−0.19***
	(−4.37)	(−4.60)	(−4.47)
ln(Family TNA)	0.02	0.03	0.04
	(0.60)	(0.63)	(0.89)
Expense ratio	0.09	0.09	0.08
	(1.26)	(1.51)	(1.23)
Fund age	−0.13***	−0.13***	−0.14***
	(−5.37)	(−5.29)	(−5.60)
Time effects	Yes	Yes	Yes
Style effects	Yes	Yes	Yes
Standardized coef.	Yes	Yes	Yes

New money growth (NMG) is measured as $\frac{TNA_{i,t+1} - TNA_{i,t}(1+R_{i,t+1})}{TNA_{i,t}(1+R_{i,t+1})} \times 100$ where $TNA_{i,t}$ is the total net assets of fund i in month t and $R_{i,t+1}$ is the return of fund i from month t to $t+1$. Coskewness (γ) and alpha are estimated daily using the past 5 years of returns over the time period September 1, 1998 through June 30, 2014. We use the estimates on the last trading day of each month. Panel A presents flows in each bin of a 5 × 5 sort on alpha and coskewness, where funds are sorted monthly. Quintiles 1 and 5 indicate the lowest and highest values, respectively. Panel B presents linear regressions of flows on alpha and coskewness and controls, including fund characteristics, style dummies, and time effects. $InstFund$ is an indicator equal to 1 if, over the life of the fund, the proportion of assets in institutional shares is above the median, and zero otherwise. Expense ratio is the ratio of the management fees and funds expenses to total net assets. Family TNA is the total net assets of the fund's family. Style classifications are based on funds' holdings. At each reporting date, we assign each stock to size, book-to-market, and momentum quintiles based on Russ Wermer's stock assignment file. For each characteristic and each fund, we value weight the rankings and average across reporting dates. We sort funds into terciles on each characteristic and intersect the sorts. Coefficients are standardized for interpretation. Standard errors are clustered by fund and by month. Statistical significance is represented by * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

and coskewness are each standardized to have unit standard deviations. We also control for time and style effects as well as fund and family TNA, expense ratio, and fund age. Both coskewness and alpha are related to new money growth, and the point estimate for coskewness is about 17% of the effect associated with alpha.

Thus, managers are penalized for a fund's undesirable coskewness in terms of reduced new money growth. Ibert, Kaniel, Van Nieuwerburgh, and Vestman (2017) provide evidence that fund managers are compensated directly as a function of assets under management, so managers should care about minimizing undesirable coskewness, all else equal. At the same time, we observe that most funds exhibit negative coskewness. Of course, the trade-off shown in Section 2 implies that this undesirable coskewness is associated with desirable alpha.

Del Guercio and Reuter (2014) show that flows to funds distributed to retail investors through brokers are less sensitive to performance than funds that are not sold through brokers. This suggests that more sophisticated investors are more responsive to performance. To investigate this possibility, we segment our sample of funds into institutional and retail funds. We identify funds as institutional funds if the fund's average proportion of assets under management in institutional share classes is above median. Institutions are more sophisticated investors, so we expect that institutional funds will have flows that are more sensitive to coskewness. Column 3 of panel B of Table 10 reports flow-performance regressions in which we interact the performance measures with an institutional fund indicator variable. Consistent with our conjecture, flows for institutional funds are 26% more sensitive to performance in terms of alpha but 83% more sensitive to performance in terms of coskewness.[25]

Given that flows to institutional funds show greater sensitivity to coskewness, we expect institutional funds to exert more effort to manage coskewness, thereby reducing the amount of undesirable coskewness per unit of alpha achieved. To check this, we split the sample of funds and regress coskewness on alpha in each subset. Controlling for styles like we do in Column 3 of Table 5, the estimated trade-off between coskewness and alpha in institutional funds is only -0.44 with a t-stat of -0.83. This is less than half of the estimated trade-off in the full sample of -0.97 and is not statistically different from zero. The coskewness costs associated with alpha are larger in retail funds, for which flows are less sensitive to coskewness. For these funds, the estimated trade-off is -1.21 with a t-stat of -3.26.

5. How Much Does Coskewness Matter to Investors?

It is important to assess whether the dispersion in coskewness across funds is large enough to matter to investors. First, we consider differences in abnormal return performance associated with coskewness relative to other characteristics of funds. Then, we analyze the price of coskewness both theoretically and

[25] For both sets of funds, the sensitivity to coskewness is small compared to the sensitivity to alpha, given the empirical trade-off between coskewness and alpha found in stocks and in funds. This indicates that funds should maximize alpha at the expense of coskewness, up to the limits imposed by leverage constraints, tracking error concerns, and other frictions.

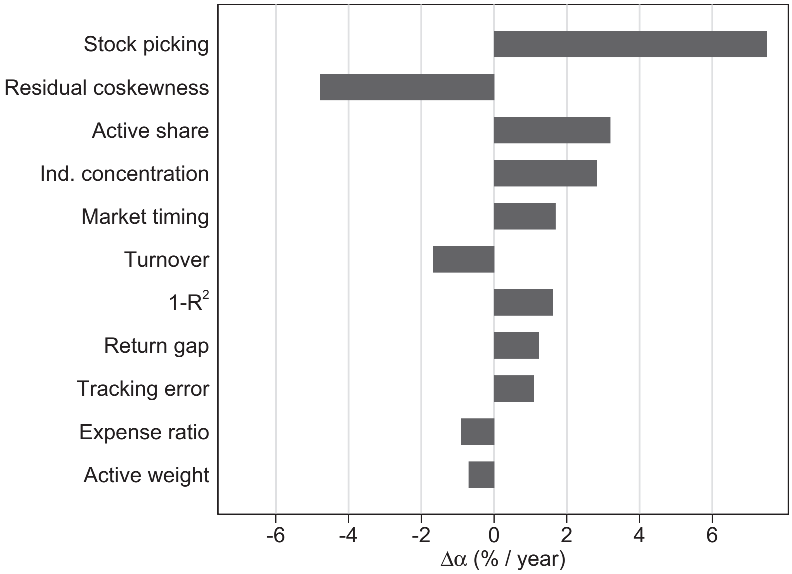


Figure 1
Economic magnitude of coskewness relative to other fund characteristics
Alpha and coskewness are estimated for 3,001 active mutual funds over the time period September 1, 1998 through June 30, 2014, using the full sample of daily returns. For each characteristic, we sort funds into quartiles on that characteristic. The figure plots the difference in average annual alphas of the 4th quartile and the 1st quartile (Q4−Q1). Expense ratio is the average expense ratio for each fund as reported by CRSP. Turnover is the average fund turnover as reported by CRSP. Active share and tracking error are the averages taken through 2009 as reported in the data from Antti Petajisto. Industry concentration, Active weight, Return gap, and $1-R^2$ are calculated like in Kacperczyk, Sialm, and Zheng (2005), Doshi, Elkamhi, and Simutin (2015), Kacperczyk, Sialm, and Zheng (2008), and Amihud and Goyenko (2013), respectively. Market timing and Stock picking are calculated like in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014).

empirically. We use the empirical price of coskewness to adjust performance of funds and portfolios of funds formed from sorts on activity measures.

5.1 Abnormal returns of funds sorted on coskewness

One way to measure the economic importance of coskewness is to compare the difference in abnormal returns associated with coskewness to similar differences associated with other fund characteristics. Figure 1 reports differences in alphas associated with moving from the first quartile to the fourth quartile of coskewness and moving from the first quartile to the fourth for other fund characteristics. We use the time-series average of these characteristics for each fund and sort funds once rather than dynamically. The difference in alpha between the bottom and top coskewness quartiles of funds is 4.8% per year. It is important to note that all of the characteristics are calculated ex post; in particular, Stock picking equals the realized stock picking returns as defined by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). It is unsurprising that successful stock pickers have high alphas, as shown in Figure 1. The difference in alpha for funds sorted on coskewness is larger than the difference created by sorting on any of the other characteristics well known to be associated with alpha (Active share, Return gap, Industry concentration, etc.).

5.2 Theoretical price of coskewness

Dahlquist, Farago, and Tédongap (2017) show that return asymmetries matter much more to investors who have the generalized disappointment aversion (GDA) preferences of Routledge and Zin (2010) than they do to constant relative risk aversion (CRRA) investors. For GDA preferences, the certainty equivalent x of a return R is the implicit solution of the equation:

$$U(x) = \mathsf{E}[U(R)] - \ell \mathsf{E}\left[(U(kx) - U(R)) 1_{\{R<kx\}}\right], \tag{10}$$

where the utility function U is given by

$$U(R) = \begin{cases} \frac{R^{1-\theta}}{1-\theta} & \text{if } \theta \neq 1 \text{ and } \theta > 0 \\ \ln R & \text{if } \theta = 1. \end{cases} \tag{11}$$

The preference parameters are risk aversion θ, aversion to disappointment ℓ, and the disappointment threshold k. In Appendix B, we calculate the approximate marginal trade-off between alpha and coskewness for a GDA representative investor when the skewness of returns is as modeled by Dahlquist, Farago, and Tédongap (2017).

Figure 2 shows the trade-off for different levels of risk aversion, the disappointment threshold, and disappointment aversion. Specifically, the figure shows the amount of alpha on an annual basis that corresponds to a one-standard-deviation change in coskewness. Disappointment aversion $\ell = 0$ corresponds to CRRA utility, and in that case, the cost of coskewness is small. However, with nonzero disappointment aversion, the cost of coskewness can be large. For example, with disappointment aversion equal to 1, a disappointment threshold of $k = 0.98$, and risk aversion $\theta = 4$, a one-standard-deviation change in coskewness is equivalent to an annual alpha of about 2.5%.

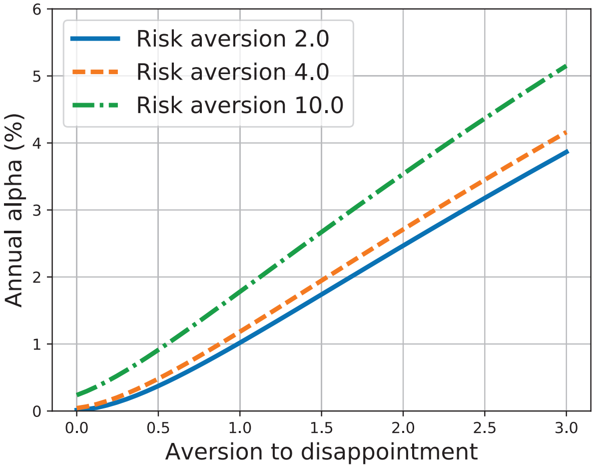
5.3 Empirical price of coskewness

Consider the quadratic regression (5) for a return R_i with coefficients a_i, b_{i1}, and b_{i2}. As explained in Appendix A, the coskewness pricing model implies that

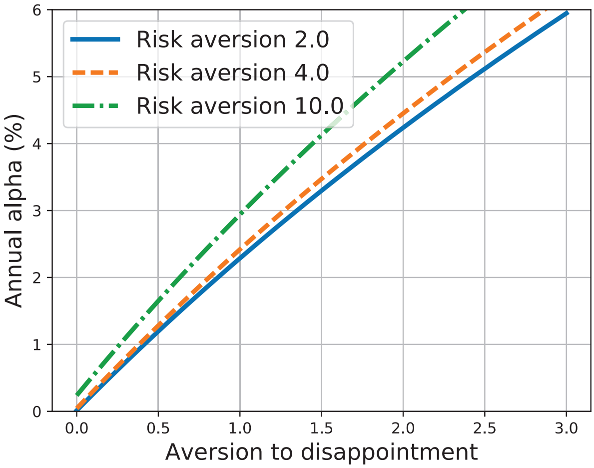
$$a_i = \psi b_{i2}, \tag{12}$$

where $\psi < 0$.

Of course, we have to estimate ψ because the second factor $(R_{mt} - R_{ft})^2$ in the quadratic regression is not a return or an excess return; hence, its price of risk is not known a priori. One possibility is to try to replace $(R_{mt} - R_{ft})^2$ with the excess return that is most highly correlated with it. Moreno and Rodríguez (2009) construct a coskewness factor that is motivated



(a) Disappointment threshold k=1



(b) Disappointment threshold k=0.98

Figure 2
Preferences and economic magnitude of coskewness
The plotted trade-off estimates denote the amount of alpha as a percentage per year required as compensation for a one-standard-deviation increase in coskewness ($0.17\%^3$ per day). The trade-offs are calculated using generalized disappointment aversion preferences where log returns are normal-exponential like in Dahlquist, Farago, and Tédongap (2017). The preference parameters are risk aversion, aversion to disappointment (ℓ), and the disappointment threshold (k). The case of ℓ=0 corresponds to expected utility under CRRA. Appendix B provides details on the calculation.

in this way.[26] Instead, we run the time series regressions (5) and then run the cross-sectional regression

$$\hat{a}_i = \psi \hat{b}_{i2} + u_i \,. \tag{13}$$

This regression is subject to errors-in-variables bias, because we have generated regressors. As is standard, we can reduce the bias by using portfolios, for which the betas b_{i2} are estimated more precisely than they are for individual stocks. We combine the sets of stock portfolios shown in Table 2 into a single cross-section, and we estimate ψ from the regression (13) over that cross-section.[27] With returns expressed as decimals, the estimated value of ψ is -3.122×10^{-4} (t-stat equal to -34.7).[28] Based on the cross-sectional standard deviation of 0.17%^{3}, a one-standard-deviation change in coskewness produces an adjustment in alpha of 2.5% on an annual basis.

5.4 Adjusted alphas

Given an estimate $\hat{\psi}$ of ψ and given the estimated coefficients $\hat{a}_i$ and $\hat{b}_{i2}$ from the time-series regressions (5), we compute an adjusted alpha for each fund i as

$$\alpha_{i,\text{adj}} = \hat{a}_i - \hat{\psi} \hat{b}_{i2} \,. \tag{14}$$

To understand why this is an adjusted alpha, note that (5) and (12) imply that

$$\begin{aligned} a_i - \psi b_{i2} &= a_i - \phi_2 b_{i2} + \mathsf{E}[(R_m - R_f)^2] b_{i2} \\ &= \mathsf{E}[R_i - R_f] - b_{i1} \mathsf{E}[R_m - R_f] - \phi_2 b_{i2} \,. \end{aligned} \tag{15}$$

Thus, the adjusted alpha is the risk premium of the fund minus the risk premium that should be earned given exposures b_{i1} and b_{i2} to the market excess return and to the squared market excess return. We show in Appendix A that the regression coefficient b_{i2} is proportional to coskewness as defined in (2), with a proportionality coefficient that depends only on market moments. Hence, the term $-\phi_2 b_{i2}$ in (15) represents a penalty or reward for coskewness.

Using the estimated value of ψ, the sample moments of the market excess return, and the formula (A7) that relates the regression coefficient b_{i2} to coskewness γ_i, we obtain

$$-\phi_2 b_{i2} = 5.77 \gamma_i$$

when we express alpha in basis points and coskewness in %^{3}. Figure 3 plots the distribution of adjusted alphas relative to CAPM alphas. The largest effects

[26] Internet Appendix C compares alpha adjustments based on our empirically estimated price of coskewness to alpha adjustments based on coskewness factors.

[27] We do not use mutual funds to estimate ψ, because we ultimately want to see whether mutual funds outperform, meaning that they earn more alpha than they should given their coskewness. If we exclusively used funds to estimate how much alpha should be earned from coskewness, then by construction half of the funds would outperform and half would underperform.

[28] We find similar estimates across the four sets of stock portfolios. The estimated ψ's are -2.9×10^{-4}, -3.2×10^{-4}, -3.9×10^{-4}, and -3.2×10^{-4} for the size/book-to-market, size/investment, size/momentum, and size/profitability sorted portfolios, respectively. All are statistically significant at the 1% level.

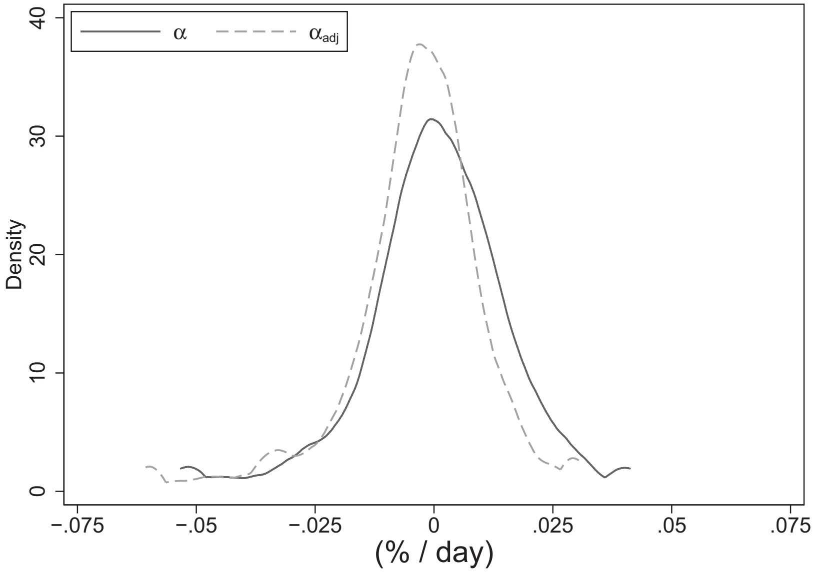


Figure 3
Densities of alpha and coskewness-adjusted alpha
Alpha (α) and coskewness-adjusted alpha (α_{adj}) are estimated for 3,001 active mutual funds over the time period September 1, 1998 through June 30, 2014, using daily returns. Alphas adjusted for coskewness are calculated as described in Section 5. $\hat{\alpha}$ and $\hat{\alpha}_{\text{adj}}$ are measured as a percentage per day.

of the adjustments are visible in the right tail of the distribution, which shifts leftward relative to the unadjusted alpha distribution. Table IA.6 in the Internet Appendix reports additional statistics concerning the adjusted alphas. Most adjusted alphas (59%) are negative, whereas a slight majority of the unadjusted alphas are positive. The median fund has an adjusted alpha of -0.63% on an annual basis. In one-tailed tests, fewer funds have significantly positive alphas (net of fees) than the size of the test, which is not true for unadjusted alphas.[29]

Finally, we revisit the profitability of mutual fund activities (net of fees) after adjusting for their coskewness costs. We replicate Table 3 using the adjusted alphas and report the results in Table 11. Importantly, when performance is adjusted for coskewness, the adjusted alphas of the high-minus-low portfolios are statistically insignificant in all but one case (Active weight). The point estimates of adjusted alpha remain positive in all cases, but the reductions in alpha are meaningful. On average, they are reduced by 37%. The largest reductions are in Active share, Return gap, and $1-R^2$. This is consistent with the strong relation observed between these activity measures and coskewness

[29] To estimate the standard error of adjusted alpha calculated in (14), we apply the delta method to the fund-specific covariance matrix obtained from model (5).

Table 11
Activity measures and adjusted alphas

	Industry concentration	Return gap	Active share	$1-R^2$	Skill index	Active weight
Decile	$\hat{\alpha}_{adj}$	$\hat{\alpha}_{adj}$	$\hat{\alpha}_{adj}$	$\hat{\alpha}_{adj}$	$\hat{\alpha}_{adj}$	$\hat{\alpha}_{adj}$
Lo	−0.46	−0.54	−0.61	−0.48	−0.57	−0.60
2	−0.45	−0.27	−0.48	−0.62	−0.75	−0.49
3	−0.56	−0.07	−0.29	−0.37	−0.68	−0.21
4	−0.31	−0.07	−0.42	−0.54	−0.48	−0.38
5	−0.31	−0.15	−0.12	−0.35	−0.28	−0.24
6	−0.03	−0.24	0.03	−0.21	−0.19	−0.27
7	−0.29	−0.08	0.15	−0.07	−0.15	−0.06
8	0.01	−0.09	0.57	0.26	0.09	−0.06
9	0.41	0.12	0.45	0.20	0.57	0.14
Hi	0.26	0.02	0.65	0.28	0.99	0.37
Hi-lo	0.71	0.56	1.26	0.76	1.56	0.98**
t(Hi-lo)	(1.13)	(0.72)	(1.23)	(1.18)	(1.11)	(2.34)
% reduction from CAPM α	−39%	−48%	−45%	−61%	−23%	−6%

Daily return series are formed by quarterly sorts of funds based on a given activity measure. Alphas adjusted for coskewness are calculated as described in Section 5 using each decile's resultant daily return series. The activity measures are described in Table 3. The sample period is September 1, 1998 through June 30, 2014, for all activity measures except Active share. The Active share decile time-series run from 1998 to 2009, because the Active share data obtained from Antti Petajisto's Web site are only available until 2009. $\hat{\alpha}_{adj}$ is measured in basis points (*bps*) per day. Statistical significance is represented by * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

shown in Table 3. Overall, there is little evidence that funds offer investors a net-of-fee way to outperform the market after taking into account their coskewness performance.

6. Conclusion

Coskewness is an important attribute of performance, and it is negatively correlated with alpha in the cross-section of fund returns. Thus, at least part of the value of the alpha of an actively managed mutual fund is typically offset by an undesirable effect on portfolio skewness. We study the determinants of fund coskewness. Coskewness is positively related to market timing and negatively related to the illiquidity of the fund's assets. Derivative usage also affects coskewness, consistent with funds writing covered calls on individual stocks (lowering coskewness) and buying protective puts on the market (increasing coskewness). There is a clear trade-off between CAPM alphas and coskewness. This trade-off is predominantly driven by stock picking. Fund characteristics that earn alpha and are associated with stock picking carry significant coskewness costs. In fact, portfolios formed from sorts on stock picking characteristics exhibit larger trade-offs than what we observe for stock portfolios on average.

It appears that investors care about coskewness. Money flows to funds with desirable coskewness. Perhaps unsurprisingly, the sensitivity of flows to coskewness is stronger for funds with more ownership by institutional investors, who are likely more sophisticated than retail investors.

Empirically, the difference in alpha between the bottom and top coskewness quartiles of funds is 4.8% per year. We estimate the price of coskewness and adjust alphas for coskewness. Fewer funds have significantly positive adjusted alphas (net of fees) than the size of the test, which is not true for unadjusted alphas. Adjustments to alphas reflecting the cost of coskewness also substantially reduce the abnormal performance of high-low portfolios formed from sorts on activity measures.

Moments beyond mean, variance, and skewness may also be important for performance evaluation. For instance, decreasing absolute prudence (Kimball 1990) implies a negative fourth derivative of the utility function and hence a preference for lower kurtosis (see also Haas 2007). In unreported results, we extend our analysis to cokurtosis, which governs a fund's marginal contribution to a benchmark portfolio's kurtosis. Negative cokurtosis funds are attractive because adding them to a portfolio reduces portfolio kurtosis. Under the coskewness/cokurtosis pricing model, positive alpha funds should be undesirable on coskewness and/or cokurtosis. We find no evidence of a trade-off between alpha and cokurtosis. In terms of higher moments, the primary cost of seeking alpha seems to be its skewness consequence.

Appendix A. The Coskewness Pricing Model

We can write the coskewness pricing model as a formula for the risk premium of an asset, as a formula for the CAPM alpha of the return or as a formula for the intercept in the quadratic regression (5). The usual statement of the model is the following formula for the risk premium: For some $\lambda_1 > 0$ and $\lambda_2 < 0$ and for all returns R,

$$\mathsf{E}[R]-R_f=\lambda_1 \operatorname{cov}(R-R_f, R_m-R_f)+\lambda_2 \operatorname{cov}\Big(R-R_f,(R_m-R_f)^2\Big). \tag{A1}$$

First, we show that this relation implies

$$\alpha=\lambda_2 \operatorname{cov}\Big(\varepsilon,(R_m-R_f)^2\Big), \tag{A2}$$

where α is the intercept and ε is the residual in the market-model regression. Thus, the CAPM alpha is linearly related to coskewness as defined in (2). More generally, whenever there is a two-factor pricing model with one of the factors being the market return, then there is a linear relation between the CAPM alpha and the covariance of the market-model residual with the second factor. To see this, let Z denote the second factor and assume

$$\mathsf{E}[R]-R_f=\lambda_1 \operatorname{cov}(R-R_f, R_m-R_f)+\lambda_2 \operatorname{cov}\big(R-R_f, Z\big). \tag{A3}$$

Substitute $R=R_f+\alpha+\beta(R_m-R_f)+\varepsilon$ to calculate the right-hand side of (A3) as

$$\begin{aligned}&\lambda_1 \operatorname{cov}(\beta R_m+\varepsilon, R_m)+\lambda_2 \operatorname{cov}(\beta R_m+\varepsilon, Z)\\ &=\beta\big[\lambda_1 \operatorname{var}(R_m)+\lambda_2 \operatorname{cov}(R_m, Z)\big]+\lambda_2 \operatorname{cov}(\varepsilon, Z).\end{aligned} \tag{A4}$$

Substitute this into (A3) and apply (A3) for the return $R=R_m$ (with $\beta=1$ and $\varepsilon=0$) to see that the expression in square braces in (A4) is the market risk premium. Thus,

$$\mathsf{E}[R]-R_f=\beta\big(\mathsf{E}[R_m]-R_f\big)+\lambda_2 \operatorname{cov}(\varepsilon, Z).$$

Subtracting $\beta\big(\mathsf{E}[R_m]-R_f\big)$ from both sides gives

$$\alpha=\lambda_2 \operatorname{cov}(\varepsilon, Z). \tag{A5}$$

Now, we derive the formula (12) for the intercept in the quadratic regression (5). The vector of multiple regression betas in (5)—dropping the i subscript denoting the asset—is $b=(b_1, b_2)'$, where b is Σ^{-1} times the vector of covariances of the excess return $R-R_f$ with the two regressors R_m-R_f and $(R_m-R_f)^2$ and where Σ is the covariance matrix of the two regressors. Hence, we can define $\phi=\Sigma\lambda$ and deduce from (A1) that

$$\mathsf{E}[R]-R_f=\phi_1 b_1+\phi_2 b_2. \tag{A6}$$

For $R=R_m$, we have $b_1=1$ and $b_2=0$, so (A6) implies $\phi_1=\mathsf{E}[R_m-R_f]$. Therefore, under the coskewness pricing model, (12) holds where $\psi=\phi_2-\mathsf{E}[(R_m-R_f)^2]$.

Finally, we observe that b_2 is proportional to coskewness as defined in (2); hence, (12) implies that the intercept in the quadratic regression is proportional to coskewness. This follows from the Frisch-Waugh Theorem, which states that the multivariate regression coefficient b_2 is the coefficient from a univariate regression of residuals on residuals, specifically, from a regression of the market model residual ε on the residual from a regression of $(R_m-R_f)^2$ on R_m-R_f. Therefore, b_2 equals $\text{cov}(\varepsilon,(R_m-R_f)^2)$ divided by the variance of the residual from the regression of $(R_m-R_f)^2$ on R_m-R_f. To be precise,

$$b_2=\frac{\text{cov}(\varepsilon,(R_m-R_f)^2)}{[1-\text{corr}(R_m-R_f,(R_m-R_f)^2)^2]\,\text{var}((R_m-R_f)^2)}. \tag{A7}$$

Appendix B. The Trade-off under Generalized Disappointment Aversion

We adopt the normal-exponential return model of Dahlquist, Farago, and Tédongap (2017). In that model, the log market return is[30]

$$\log R_m=\mu_m+\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\,\xi_m. \tag{B1}$$

Here, ξ_0 is exponentially distributed with parameter 1, and ξ_m is an independent standard normal random variable. All assets are subject to the same exponentially distributed shock ξ_0, but each has its own normally distributed shock (the normal shocks can be correlated across assets). We consider an asset with a standard normal shock ξ and write

$$\xi=\rho\xi_m+\sqrt{1-\rho^2}\,u$$

for a standard normal u that is independent of ξ_m. Of course, $\rho\in[-1,1]$ is the correlation between ξ_m and ξ. With this notation, the log return of the asset is

$$\log R=\mu+\sigma\delta\xi_0+\sigma\rho\sqrt{1-\delta^2}\,\xi_m+\sigma\sqrt{(1-\delta^2)(1-\rho^2)}\,u. \tag{B2}$$

The SDF for generalized disappointment aversion is proportional to the marginal utility

$$R_m^{-\theta}\left(1+\ell 1_{\{R_m/x_m<k\}}\right) \tag{B3}$$

where x_m is the certainty equivalent of R_m, $k\leq 1$ denotes the threshold for disappointment (disappointment occurs when $R/x<k$) and $\ell\geq 0$ represents the aversion to disappointment ($\ell=0$ is expected utility). The certainty equivalent x_m is the implicit solution of the equation

$$x_m^{1-\theta}=\mathsf{E}[R_m^{1-\theta}]-\ell\mathsf{E}\left[\left(k^{1-\theta}x_m^{1-\theta}-R_m^{1-\theta}\right)1_{\{R_m/x_m<k\}}\right] \tag{B4}$$

where θ denotes risk aversion. We analyze this equation further below.

[30] Here, we write μ_m for what is $\mu_m-\sigma_m\delta_m$ in Dahlquist, Farago, and Tédongap (2017). In general, to recover their μ from ours, add $\sigma\delta$ to ours. Their convention implies that μ is the mean log return, but that convention is not useful for us.

Let M denote the SDF. Because M is proportional to (B3), imposing $E[M]=1/R_f$ implies

$$M=\frac{R_m^{-\theta}(1+\ell 1_{\{R_m/x_m<k\}})}{R_f\,\mathsf{E}[R_m^{-\theta}(1+\ell 1_{\{R_m/x_m<k\}})]}.$$

The condition $\mathsf{E}[R_m M]=1$ implies

$$\mathsf{E}[R_m^{1-\theta}(1+\ell 1_{\{R_m/x_m<k\}})]=R_f\,\mathsf{E}[R_m^{-\theta}(1+\ell 1_{\{R_m/x_m<k\}})].$$

This implies

$$\begin{aligned}\mu_m=&\log R_f+\log\mathsf{E}\left[\mathrm{e}^{-\theta\left\{\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\,\xi_m\right\}}(1+\ell 1_{\{R_m/x_m<k\}})\right]\\ &-\log\mathsf{E}\left[\mathrm{e}^{(1-\theta)\left\{\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\,\xi_m\right\}}(1+\ell 1_{\{R_m/x_m<k\}})\right].\end{aligned}\tag{B5}$$

The condition $\mathsf{E}[RM]=1$ implies

$$\mathsf{E}[RR_m^{-\theta}(1+\ell 1_{\{R_m/x_m<k\}})]=R_f\,\mathsf{E}[R_m^{-\theta}(1+\ell 1_{\{R_m/x_m<k\}})].$$

This implies

$$\begin{aligned}\mu=&\log R_f+\log\mathsf{E}\left[\mathrm{e}^{-\theta\left\{\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\,\xi_m\right\}}(1+\ell 1_{\{R_m/x_m<k\}})\right]\\ &-\log\mathsf{E}\left[\left(\mathrm{e}^{(\sigma\delta-\theta\sigma_m\delta_m)\xi_0+\left(\sigma\rho\sqrt{1-\delta^2}-\theta\sigma_m\sqrt{1-\delta_m^2}\right)\xi_m+\sigma\sqrt{(1-\delta^2)(1-\rho^2)}\,u}\right)\right.\\ &\left.\times\left(1+\ell 1_{\{R_m/x_m<k\}}\right)\right].\end{aligned}\tag{B6}$$

We can calculate μ_m from (B5) and μ from (B6) given R_f and the other parameters.

We can rearrange equation (B4) for the certainty equivalent as

$$\mathsf{E}\left[\left(\frac{R_m}{x_m}\right)^{1-\theta}\right]=1+\ell\,\mathsf{E}\left[\left(k^{1-\theta}-\left(\frac{R_m}{x_m}\right)^{1-\theta}\right)1_{\{R_m/x_m<k\}}\right].\tag{B7}$$

Clearly, x_m is homogeneous of degree 1 in R_m. This means that the ratio R_m/x_m is invariant with respect to μ_m. Define ψ_m by $\mathrm{e}^{\psi_m}=\mathrm{e}^{\mu_m}/x_m$. Then,

$$\frac{R_m}{x_m}=\mathrm{e}^{\psi_m+\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\,\xi_m}.\tag{B8}$$

We can rewrite (B7) as

$$\begin{aligned}&\mathrm{e}^{(1-\theta)\psi_m}\,\mathsf{E}\left[\mathrm{e}^{(1-\theta)\left(\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\,\xi_m\right)}\left(1+\ell 1_{\{R_m/x_m<k\}}\right)\right]\\ &=1+\ell k^{1-\theta}\,\mathsf{E}\left[1_{\{R_m/x_m<k\}}\right].\end{aligned}\tag{B9}$$

The parameter ψ_m is given implicitly by (B9).

The event $R_m/x_m < k$ that appears in (B5), (B6) and (B9) is the event

$$\sigma_m \delta_m \xi_0 + \sigma_m \sqrt{1-\delta_m^2}\,\xi_m < \log k - \psi_m .$$

The cases $\delta_m < 0$, $\delta_m > 0$, and $\delta_m = 0$ must be addressed separately. Set

$$d_m = \frac{\log k - \psi_m}{\sigma_m \sqrt{1-\delta_m^2}}$$

and

$$\phi_m = \frac{\sqrt{1-\delta_m^2}}{\delta_m} .$$

If $\delta_m < 0$, then the event is equivalent to $\xi_0 > \phi_m(d_m - \xi_m)$ and this occurs for sure if $\phi_m(d_m-\xi_m) < 0$, which is equivalent to $\xi_m < d_m$ (because $\phi_m < 0$ when $\delta_m < 0$). Thus, we have

$$\delta_m < 0 \quad \Rightarrow \quad 1_{\{R_m/x_m<k\}} = 1_{\{\xi_m<d_m\}} + 1_{\{\xi_m>d_m\}} \cdot 1_{\{\xi_0>\phi_m(d_m-\xi_m)\}} . \tag{B10}$$

Now, suppose $\delta_m > 0$. In that case, the event is equivalent to $\xi_0 < \phi_m(d_m - \xi_m)$, and that cannot occur unless $\xi_m < d_m$. Therefore,

$$\delta_m > 0 \quad \Rightarrow \quad 1_{\{R_m/x_m<k\}} = 1_{\{\xi_m<d_m\}} \cdot 1_{\{\xi_0<\phi_m(d_m-\xi_m)\}} . \tag{B11}$$

For the case $\delta_m = 0$, set

$$d_{m0} = \frac{\log k - \psi_m}{\sigma_m} .$$

We have

$$\delta_m = 0 \quad \Rightarrow \quad 1_{\{R_m/x_m<k\}} = 1_{\{\xi_m<d_{m0}\}} . \tag{B12}$$

We use the characterizations (B10), (B11), and (B12) and iterated expectations (conditioning first on ξ_m) to calculate ψ_m as a fixed point of (B9) and then to calculate μ_m from (B5) and μ from (B6).

The expectations that appear in (B5), (B6), and (B9) are all of the form

$$\mathsf{E}\left[e^{a\xi_0+b\xi_m+cu}\right]$$

or the form

$$\mathsf{E}\left[e^{a\xi_0+b\xi_m+cu} 1_{\{R_m/x_m<k\}}\right] .$$

For the former, we use independence and the moment generating functions of normal and exponential variables to obtain

$$\mathsf{E}\left[e^{a\xi_0+b\xi_m+cu}\right] = \frac{e^{b^2/2+c^2/2}}{1-a} . \tag{B13}$$

Notice that this calculation requires $a < 1$. Let N denote the standard normal distribution function. When $\delta_m < 0$, we can calculate the second type of expectation as

$$\begin{aligned} &\mathsf{E}\left[e^{a\xi_0+b\xi_m+cu} 1_{\{R_m/x_m<k\}}\right] \qquad \text{(B14)} \\ &= e^{c^2/2}\mathsf{E}\left[e^{b\xi_m} 1_{\{\xi_m<d_m\}} \mathsf{E}\left[e^{a\xi_0} \mid \xi_m\right]\right] \\ &\quad + e^{c^2/2}\mathsf{E}\left[e^{b\xi_m} 1_{\{\xi_m>d_m\}} \mathsf{E}\left[e^{a\xi_0} 1_{\{\xi_0>\phi_m(d_m-\xi_m)\}} \mid \xi_m\right]\right] \\ &= \frac{e^{c^2/2}}{1-a}\mathsf{E}\left[e^{b\xi_m} 1_{\{\xi_m<d_m\}}\right] + e^{c^2/2}\mathsf{E}\left[e^{b\xi_m} 1_{\{\xi_m>d_m\}} \frac{e^{(a-1)\phi_m(d_m-\xi_m)}}{1-a}\right] \\ &= \frac{e^{b^2/2+c^2/2}}{1-a}\mathrm{N}(d_m-b) + \frac{e^{c^2/2+(a-1)\phi_m d_m}}{1-a}\mathsf{E}\left[e^{[b-(a-1)\phi_m]\xi_m} 1_{\{\xi_m>d_m\}}\right] \end{aligned}$$

$$=\frac{e^{b^2/2+c^2/2}}{1-a}\mathrm{N}(d_m-b)+\frac{e^{c^2/2+(a-1)\phi_m d_m}}{1-a}\mathsf{E}\left[e^{[(a-1)\phi_m-b](-\xi_m)}1_{\{-\xi_m<-d_m\}}\right]$$

$$=\frac{e^{b^2/2+c^2/2}}{1-a}\mathrm{N}(d_m-b)+\frac{e^{[(a-1)\phi_m-b]^2/2+c^2/2+(a-1)\phi_m d_m}}{1-a}\mathrm{N}(b-(a-1)\phi_m-d_m). \quad \text{(B15)}$$

For the third and fifth equalities, we used the fact that if z is a standard normal, then for any α and β, $\mathsf{E}[e^{\alpha z}1_{\{z<\beta\}}]=e^{\alpha^2/2}\mathrm{N}(\beta-\alpha)$. When $\delta_m>0$, we can calculate the second type of expectation as

$$\mathsf{E}\left[e^{a\xi_0+b\xi_m+cu}1_{\{R_m/x_m<k\}}\right]$$

$$=e^{c^2/2}\mathsf{E}\left[e^{b\xi_m}1_{\{\xi_m<d_m\}}\mathsf{E}\left[e^{a\xi_0}1_{\{\xi_0<\phi_m(d_m-\xi_m)\}}\,|\,\xi_m\right]\right]$$

$$=e^{c^2/2}\mathsf{E}\left[e^{b\xi_m}1_{\{\xi_m<d_m\}}\frac{1-e^{(a-1)\phi_m(d_m-\xi_m)}}{1-a}\right]$$

$$=\frac{e^{c^2/2}}{1-a}\mathsf{E}\left[e^{b\xi_m}1_{\{\xi_m<d_m\}}\right]-\frac{e^{c^2/2+(a-1)\phi_m d_m}}{1-a}\mathsf{E}\left[e^{[b-(a-1)\phi_m]\xi_m}1_{\{\xi_m<d_m\}}\right]$$

$$=\frac{e^{b^2/2+c^2/2}}{1-a}\mathrm{N}(d_m-b)-\frac{e^{[b-(a-1)\phi_m]^2/2+c^2/2+(a-1)\phi_m d_m}}{1-a}\mathrm{N}(d_m-b+(a-1)\phi_m). \quad \text{(B16)}$$

When $\delta_m=0$, then $a=0$ in the second type of expectation, and we can calculate it as

$$\mathsf{E}\left[e^{b\xi_m+cu}1_{\{R_m/x_m<k\}}\right]=e^{c^2/2}\mathsf{E}\left[e^{b\xi_m}1_{\{\xi_m<d_{m0}\}}\right]$$

$$=e^{b^2/2+c^2/2}\mathrm{N}(d_{m0}-b). \quad \text{(B17)}$$

Calculation of alphas and coskewness is straightforward. Using independence and the moment generating functions of normal and exponential variables, we can calculate $\mathsf{E}[R]$, $\mathsf{E}[R_m]$, $\mathsf{E}[RR_m]$, $\mathsf{E}[R_m^2]$, $\mathsf{E}[RR_m^2]$, $\mathsf{E}[R_m^3]$,

$$\beta=\frac{\mathsf{E}[RR_m]-\mathsf{E}[R]\mathsf{E}[R_m]}{\mathsf{E}[R_m^2]-\mathsf{E}[R_m]^2},$$

and

$$\alpha=\mathsf{E}[R]-R_f-\beta\left(\mathsf{E}[R_m]-R_f\right).$$

Coskewness is

$$\mathsf{E}[\varepsilon R_m^2]=\mathsf{E}[(R-R_f-\alpha-\beta(R_m-R_f))R_m^2]$$

$$=\mathsf{E}[RR_m^2]-\beta\mathsf{E}[R_m^3]-(R_f+\alpha-\beta R_f)\mathsf{E}[R_m^2]. \quad \text{(B18)}$$

For these calculations, we use

$$R=e^{\mu+\sigma\delta\xi_0+\sigma\rho\sqrt{1-\delta^2}\xi_m+\sigma\sqrt{(1-\delta^2)(1-\rho^2)}u},$$

$$R_m=e^{\mu_m+\sigma_m\delta_m\xi_0+\sigma_m\sqrt{1-\delta_m^2}\xi_m},$$

$$RR_m=e^{\mu+\mu_m+(\sigma\delta+\sigma_m\delta_m)\xi_0+\left(\sigma\rho\sqrt{1-\delta^2}+\sigma_m\sqrt{1-\delta_m^2}\right)\xi_m+\sigma\sqrt{(1-\delta^2)(1-\rho^2)}u},$$

$$R_m^2=e^{2\mu_m+2\sigma_m\delta_m\xi_0+2\sigma_m\sqrt{1-\delta_m^2}\xi_m},$$

$$RR_m^2=e^{\mu+2\mu_m+(\sigma\delta+2\sigma_m\delta_m)\xi_0+\left(\sigma\rho\sqrt{1-\delta^2}+2\sigma_m\sqrt{1-\delta_m^2}\right)\xi_m+\sigma\sqrt{(1-\delta^2)(1-\rho^2)}u},$$

$$R_m^3=e^{3\mu_m+3\sigma_m\delta_m\xi_0+3\sigma_m\sqrt{1-\delta_m^2}\xi_m}.$$

We can calculate the certainty equivalent for any return (B2) in exactly the same way we calculated the certainty equivalent for the market return. Specifically, we solve equation (B9) for ψ, dropping the m subscripts throughout. Correlation with the market is not important for this calculation, so there is no loss of generality in taking $\rho = 1$, as is implicit in (B9). Given μ (which does depend on ρ) calculated from (B6), the certainty equivalent is $x = \mathrm{e}^{\mu-\psi}$.

Because we used marginal utility at the market return as the SDF in calculating expected returns, the market return is optimal for the investor. This implies that the derivatives of the certainty equivalent with respect to the parameters σ and δ of a return must be zero at the market values σ_m and δ_m. We can regard the certainty equivalent x as at least approximately determined by the α and γ (coskewness) of a return. Then we can calculate

$$0 = \left.\frac{\mathrm{d}x}{\mathrm{d}\sigma}\right|_{\sigma=\sigma_m} \approx \left.\frac{\partial x}{\partial \alpha}\frac{\mathrm{d}\alpha}{\mathrm{d}\sigma}\right|_{\sigma=\sigma_m} + \left.\frac{\partial x}{\partial \gamma}\frac{\mathrm{d}\gamma}{\mathrm{d}\sigma}\right|_{\sigma=\sigma_m}. \tag{B19}$$

We can calculate $\mathrm{d}\alpha/\mathrm{d}\sigma$ and $\mathrm{d}\gamma/\mathrm{d}\sigma$ numerically. With these numerical values substituted into (B19), we can see how much coskewness matters at the margin compared to alpha. Specifically, the slope of the indifference curve (the amount of alpha required to compensate for a unit of coskewness) is

$$\frac{\mathrm{d}\alpha}{\mathrm{d}\gamma} = -\frac{\partial x/\partial\gamma}{\partial x/\partial\alpha} \approx \frac{\mathrm{d}\alpha/\mathrm{d}\sigma}{\mathrm{d}\gamma/\mathrm{d}\sigma}. \tag{B20}$$

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