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Looking under the Hood of Active Credit Managers

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Extensive research has explored the style exposures of actively managed equity funds. We conducted an exhaustive set of return-based and holdings-based analyses to understand actively managed credit funds. We found that credit long–short managers tend to have high passive exposure to the credit risk premium. In contrast, we found that long-only managers that focus on high-yield credits provide less exposure to the credit risk premium than do their respective benchmarks. For both credit hedge funds and long-only credit mutual funds, we found that neither has economically meaningful exposures to well-compensated systematic factors.

CE Credits: 2

The purpose of our project was to examine the behavior of actively managed credit hedge funds and mutual funds. We asked: Do actively managed credit funds deliver alpha, or are excess-of-benchmark returns simply exposures to traditional risk premiums? Ultimately, an investor should care about receiving positive excess-of-benchmark returns that are uncorrelated with whatever else is in the investor's portfolio. If an asset owner allocates to a hedge fund, the aim is to gain access to returns that are not correlated with traditional risk premiums (e.g., the Equity risk premium, Credit risk premium, and Treasury risk premium). Ideally, a full-fee hedge fund investment vehicle should hedge out market exposures (see, e.g., Asness, Krail, and Liew 2001). Similarly, if an asset owner allocates to an actively managed long-only fund, the aim is to gain access to both the traditional risk premiums embedded in the benchmark (e.g., the Credit risk premium) and active (excess-of-benchmark) returns that are not correlated with traditional risk premiums.

We examined the returns and holdings of credit hedge funds and high-yield (HY) credit mutual funds to assess whether actively managed credit funds deliver active returns that are uncorrelated with traditional risk premiums. Our analysis made use of a comprehensive set of 219 credit hedge funds covered in the live and graveyard files of Hedge Fund Research (HFR) and 96 mutual funds benchmarked to a HY corporate bond index covered by both Lipper (holdings data) and Morningstar (return data). We were able to analyze the excess returns for both sets of actively managed credit funds, but we could conduct holdings-based analysis only for the credit mutual funds, for which we had access to periodic portfolio holdings information. Our analysis covers the time period from January 1997 through June 2018—a sample of 258 months for the return analysis and 86 quarters for the holdings analysis.

We conducted two sets of analyses. First, we examined the betas of actively managed credit funds in relation to traditional risk premiums. Specifically, we considered whether the excess-of-cash returns

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of credit hedge funds exhibit any correlation with traditional risk premiums and whether the excess-of-benchmark returns of actively managed credit long-only funds exhibit any correlation with traditional risk premiums. We found in both cases no correlation, and the strength of this result is sobering. Credit hedge funds, like their equity siblings, provide meaningful (passive) exposure to traditional risk premiums. For example, across our 219 credit hedge funds, we found that nearly 50% of the median manager's time-series variation in excess-of-cash returns can be explained by passive exposure to traditional market risk premiums (covering Equity, Credit, and Treasury risk premiums). HY credit mutual funds, in contrast, provide less credit exposure than the benchmark. We found that across our 96 HY credit funds, excess-of-benchmark returns had a negative correlation (–0.25) with the Credit risk premium, suggesting that the typical HY credit mutual fund is run with a beta of 0.94 with respect to the benchmark.[1] Some investors may prefer a beta different from 1, but in any case, being aware of, and paying careful attention to, the beta exposure in one's actively managed credit allocation is important. In the case of credit hedge funds, the investor is probably getting too much passive credit exposure, and in the case of HY credit mandates, the investor is probably getting too little. The alternative, however, is to ensure that portfolio positions are *ex ante* beta neutral for credit hedge funds and *ex ante* beta equal to 1 for long-only funds.[2]

Second, we examined whether recently documented systematic investment approaches (see, e.g., Houweling and van Zundert 2017; Israel, Palhares, and Richardson 2018) were able to explain variations in excess-of-cash returns of credit hedge funds or excess-of-benchmark returns of actively managed credit long-only funds. Alternatively stated, the question is: Can a systematic approach to harvesting alternative risk premiums (e.g., valuation, momentum, carry, and defensive factors) provide returns that are uncorrelated with the returns of incumbent active credit managers?[3] It can, and the strength of this result is encouraging. Systematic approaches to investing are commonplace in equity markets, but until relatively recently, research exploring cross-sectional drivers of returns in fixed-income markets was limited, particularly so for corporate credit. With (1) the growth of the corporate bond market itself, (2) the accessibility of data, and (3) an awareness of the applicability of systematic approaches to fixed-income markets, that pattern is changing. Although recent papers (e.g., Correia, Richardson, and Tuna 2012; Chordia, Goyal, Nozawa, Subrahmanyam, and Tong 2017; Houweling and van Zundert 2017; Israel et al. 2018) have documented pervasive evidence of predictability in the cross-section of corporate bond returns, we still know little about the behavior of actively managed credit hedge funds and mutual funds.

For our sample of 219 credit hedge funds, both individually and in aggregate, we found that excess-of-cash returns exhibited low correlations with systematic valuation, momentum, carry, and defensive factors. Specifically, between 7% and 12% of the variation in excess-of-cash returns can be explained by these systematic exposures. Similarly, for our sample of 96 HY credit mutual funds, both individually and in aggregate, we found that only 2% of the variation in excess-of-benchmark returns can be explained by systematic exposures.

For a set of 154 credit mutual funds, we complemented the active return analysis with a thorough examination of holdings. Similar to what we observed in the return analysis, we found credit mutual fund active weights to be only slightly correlated, both individually and in aggregate, with systematic factor attributes. Specifically, the correlations of credit mutual fund manager active weights with standardized scores of attractiveness based on measures of valuation, momentum, carry, and defensive factors are all close to zero (i.e., we found no evidence of an active tilt toward systematic investment themes). Not surprisingly, a portfolio that is designed to target these systematic factor attributes can generate a much larger economic exposure to those attributes.

Like our first result regarding credit beta, this finding has a clear implication for investors. An allocation to a systematic credit manager together with a traditional discretionary active credit manager has the potential to be a powerful diversifier. Neither systematic nor discretionary approaches are, or even need to be, inherently superior. If both are well executed and charge fair fees, they may complement each other well in an overall active credit mandate. Our analysis suggests that excess-of-benchmark return correlations between systematic and discretionary managers are low, and excess-of-benchmark weights also exhibit low correlations.

Our article adds to the long line of research on fund manager performance. Most studies have focused on equity-oriented funds, but our research was conducted entirely on credit-oriented funds. We are aware of only a small number of papers that have examined the returns or holdings of actively managed bond funds. Of that research, all the papers examined a combination of government bond and corporate bond funds with a primary focus on return decomposition. For example, Kahn and Lemmon (2015) examined 121 fixed-income funds over a two-year period and found that, on average, two beta factors—duration and credit—explain about 67% of the time variation in their returns. Moneta (2015) and Cici and Gibson (2012) decomposed bond fund returns with a view to assessing market-timing ability and/or bond selection ability beyond rating and maturity profiles. Choi and Kronlund (2018) found evidence that bond funds tilt their portfolio weights to higher-yield securities when the yield curve is low and flat. Finally, Fung and Hsieh (2002, 2006) showed that the first principal component for 20 high-yield hedge funds explains nearly 70% of the time-series variation of their returns, which is consistent with a strong market loading (primarily explained by changes in aggregate credit spreads). Although these past papers examined the returns of actively managed bond funds, none of them cleanly answered the questions as to (1) whether excess-of-benchmark returns are additive to traditional market risk premiums and (2) whether the holdings of actively managed bond funds can be explained by systematic factor attributes.

We greatly extend this past research along several dimensions. Most actively managed mutual funds and even some hedge funds have mandates to provide both beta and active management. We carefully disentangled the two by showing, first, the importance of traditional risk premiums in explaining active credit manager fund returns and, second, the lack of importance of alternative risk premiums (value, momentum, carry, and defensive) in explaining active credit manager fund returns or holdings. We also expand both the time series and cross-section of actively managed credit funds covered. In addition, whereas most studies have focused only on returns, we also studied holdings, thus increasing the power of our analysis.

The key findings in our article are as follows. First, actively managed credit hedge funds and credit mutual funds differ substantially in their Credit risk premium exposures. Credit hedge funds provide too much exposure, when arguably they are supposed to hedge out traditional market risk premiums. Credit mutual funds provide too little exposure. In both cases, the implication for investors is to pay attention to the traditional market risk premiums embedded in their active credit manager allocations and, furthermore, to make sure that the fees they pay for that traditional market risk are appropriate (i.e., low).

Second, both actively managed credit hedge funds and credit mutual funds fail to provide any economically meaningful exposure to well-compensated systematic factors. This is not to say that a traditional discretionary approach to risk taking in credit markets is inferior. Rather, the implications for asset owners are that there is more than one way to skin a cat and that a well-executed portfolio that targets exposures to well-compensated alternative risk premiums (e.g., value, momentum, carry, and defensive) may provide powerful diversification benefits to an overall credit allocation.

Data and Methodology

In this section, we discuss our hedge fund data, the HY credit mutual fund data, and the initial return analysis for both sets of data.

Credit Hedge Fund Data and Initial Return Analysis.

For our empirical analysis of actively managed credit hedge funds, we obtained our data from the HFR Index (HFRI). For our time-series analysis of the beta and systematic exposures of actively managed credit hedge funds, we used the HFRI Relative Value: Fixed Income-Corporate Index. We obtained monthly hedge fund index return data from January 1997 through June 2018. We limited ourselves to individual funds within this HFR category that clearly took active risk in credit-sensitive assets. Specifically, we read the investment philosophy of each credit hedge fund and limited ourselves to funds that primarily focused on security selection within public credit markets. Of the 446 hedge funds within the HFRI Relative Value: Fixed Income-Corporate category, we removed 174 funds that focused on loans or had a focus outside the United States (our return data are all based on US corporate bonds). We then removed a further 53 funds that had less than 24 months of return data. The final sample of 219 funds accounts for 72% of the total assets managed within the HFRI Relative Value: Fixed Income-Corporate category. The 227 excluded funds tended to be small; average assets under management (AUM) of the excluded funds was $120 million, compared with $265 million for the 219 included funds. Notably, our key finding of a strong correlation between excess-of-cash returns and the Credit risk premium was also seen for these smaller funds, which had shorter track records or did not focus on corporate credit. Across the set of 227 excluded funds, the median correlation between excess-of-cash returns and the credit excess returns of a diversified HY index was 0.57, compared with 0.61 for the 219 included funds (the full results are discussed in the section "Detailed Return Analysis of Credit Hedge Funds"). We used net-of-fee monthly return data for individual hedge funds. To minimize survivorship bias, we examined both funds currently operating and funds that had fallen out of their respective index return series. The average credit hedge fund existed for 81 months.

Table 1, Panel A, summarizes the performance (excess-of-cash returns) of the credit hedge funds in our sample. Over this time period, the average credit hedge fund reported annualized net-of-fee and net-of-cash returns of nearly 4%. **Figure 1**, Panel A, shows the distribution of annualized net-of-fee and net-of-cash returns of the 219 individual credit hedge funds. The distribution is notably to the right of zero, and the average Sharpe ratio across the 219 funds is 0.79. At first glance, credit hedge funds appear to have delivered excellent excess-of-cash returns. The purpose of this article is to examine the source of these excess-of-cash returns.

Table 1. Active Returns of Actively Managed Credit Funds, January 1997–June 2018

			Percentile					
Year	*N*	Mean	10	25	50	75	90	Std. Dev.
A. Credit hedge funds								
1997	31	8.81%	−3.36%	−0.23%	1.75%	6.57%	11.90%	26.32%
1998	35	−7.66	−56.05	−30.96	−6.95	−2.27	1.55	5.66
1999	41	4.35	−30.84	−3.56	−1.95	2.49	9.00	30.49
2000	41	−1.19	−36.33	−16.88	−6.67	0.50	4.69	16.52
2001	42	2.93	−28.87	−18.49	0.07	3.37	6.04	16.17
2002	60	7.69	−8.84	−0.30	1.37	4.96	11.37	21.21
2003	75	13.23	−0.21	1.26	5.24	10.68	19.78	30.26
2004	86	6.22	−3.15	−0.33	2.34	5.33	8.41	13.83
2005	88	2.64	−5.63	−4.07	−0.76	0.62	4.37	8.35
2006	84	3.09	−9.63	−5.45	−1.50	2.75	5.51	11.95
2007	76	0.74	−18.08	−12.22	−3.18	1.37	5.50	18.23
2008	83	−22.92	−73.11	−62.92	−33.36	−22.11	0.69	15.05
2009	82	25.20	−16.21	−3.06	12.58	23.43	36.31	51.86
2010	88	11.44	−1.89	0.80	5.42	9.92	15.10	22.57
2011	86	1.73	−8.78	−5.89	−1.62	1.35	4.46	9.26
2012	92	10.42	−3.45	3.86	6.69	10.33	14.65	18.44
2013	91	6.24	−4.52	−0.86	2.37	7.10	9.55	14.30
2014	89	2.70	−5.33	−3.27	0.41	2.50	4.73	7.68
2015	88	−1.37	−13.32	−10.17	−5.40	−0.73	2.72	5.82
2016	91	8.79	−0.46	1.56	3.78	6.17	12.61	16.55
2017	91	4.82	−3.35	−0.83	2.33	4.45	7.47	10.16
2018	91	−1.28	−12.33	−9.23	−3.60	−1.70	2.68	5.58
Avg.	74	3.94	−15.63	−8.24	−0.94	3.50	9.05	17.10

(continued)

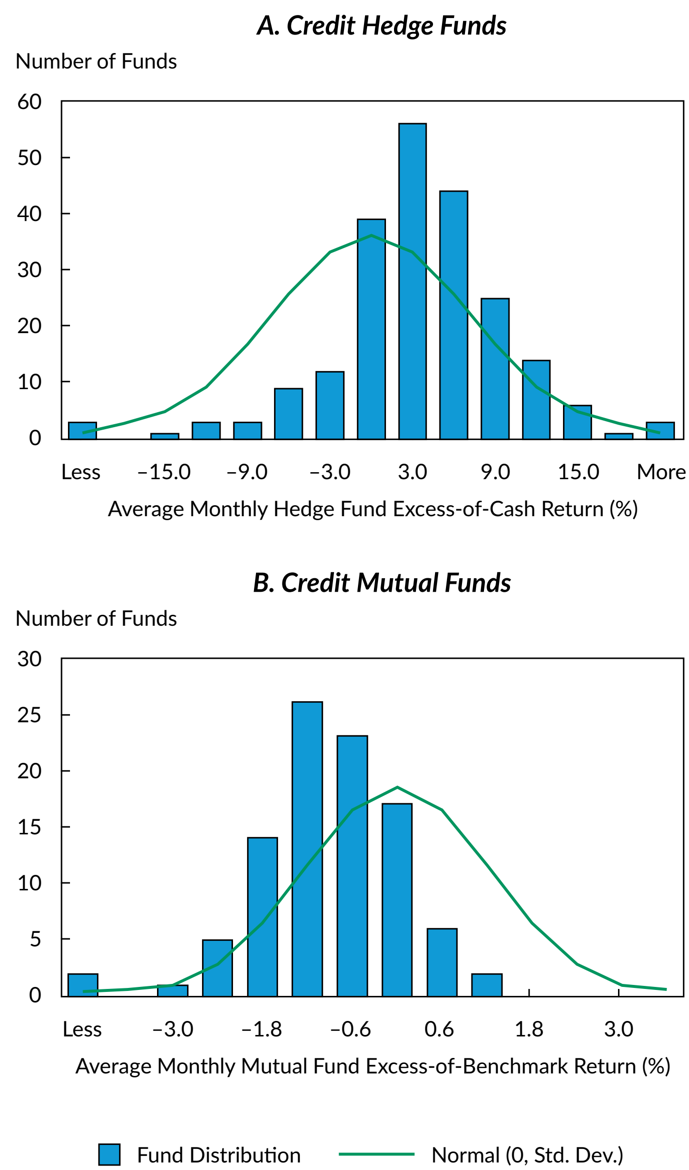
Table 1. Active Returns of Actively Managed Credit Funds, January 1997–June 2018 (continued)

			Percentile					
Year	*N*	Mean	10	25	50	75	90	Std. Dev.
B. Credit mutual funds								
1996	23	2.43%	−1.79%	−0.02%	1.86%	3.38%	8.45%	2.12%
1997	43	0.69	−1.22	−0.32	0.45	1.96	2.92	1.84
1998	53	−0.07	−4.11	−2.18	−0.54	1.66	3.50	3.67
1999	59	1.64	−2.91	0.13	2.04	4.67	6.71	2.00
2000	62	−1.14	−9.36	−4.01	−0.95	2.53	6.88	2.65
2001	66	−2.96	−7.84	−5.26	−2.04	0.25	2.16	3.18
2002	69	−1.12	−6.82	−3.96	−0.47	2.32	4.61	4.09
2003	71	−3.14	−7.32	−6.05	−3.46	−0.48	1.93	2.02
2004	74	−0.46	−2.74	−1.57	−0.55	0.08	1.25	1.27
2005	78	−0.18	−1.40	−0.74	−0.19	0.59	1.19	1.22
2006	82	−0.82	−2.45	−1.85	−0.64	0.14	0.90	0.81
2007	85	−0.39	−1.50	−0.82	−0.22	0.53	1.19	1.08
2008	84	0.14	−5.70	−2.96	1.01	5.22	7.63	4.24
2009	84	−6.44	−15.25	−8.74	−5.60	−2.00	0.70	4.06
2010	83	−0.65	−2.74	−1.72	−0.78	0.37	1.41	1.27
2011	85	−1.17	−3.12	−2.00	−0.93	−0.22	0.73	1.43
2012	88	−0.52	−2.37	−1.46	−0.57	0.50	1.78	0.98
2013	87	−0.04	−1.99	−1.10	−0.35	0.52	1.99	0.78
2014	85	−1.08	−3.07	−2.00	−0.89	−0.14	0.93	0.95
2015	85	−0.05	−2.99	−1.20	0.20	1.69	2.81	1.20
2016	84	−2.42	−4.92	−3.74	−2.49	−1.05	0.20	1.68
2017	84	−0.50	−1.69	−1.22	−0.44	0.04	0.80	0.73
2018	84	−0.67	−2.23	−1.32	−0.73	−0.01	0.54	0.74
Avg.	74	−0.82	−4.15	−2.35	−0.71	0.98	2.66	1.91

Notes: The dataset used in Panel A consists of 219 US-centric credit hedge funds in the HFRI. The dataset used in Panel B consists of 96 HY corporate bond mutual funds in our Morningstar sample. Active return is defined as return in excess of cash for hedge funds and return in excess of the reporting benchmark for mutual funds.

Active HY Credit Mutual Fund Data and Initial Return Analysis. For our empirical analysis of actively managed credit mutual funds, we obtained the data from Morningstar Direct. Specifically, we selected mutual funds in the Morningstar database with an explicit HY benchmark from one of the two most popular benchmark providers: Bank of America Merrill Lynch (BAML) and Barclays. Through this process, we identified 182 credit mutual funds. We further filtered the dataset by requiring mutual funds to have at least three years of return history, to manage at least \$50 million in corporate bond holdings in a reporting quarter, and to hold at least 80% of their corporate bond portfolio in US HY bonds. This last filter is important because some benchmarked credit mutual funds hold nontrivial positions in noncorporate bond assets (e.g., loans and equities). These positions can distort a mutual fund's excess-of-benchmark returns and introduce noise into a return analysis. After these filters were

Figure 1. Distribution of Net-of-Fee and Excess-of-Benchmark Returns across Individual Actively Managed Credit Funds, January 1997–June 2018



	Credit Hedge Funds			Credit Mutual Funds		
	Excess Return	Volatility	Sharpe Ratio	Active Return	Volatility	Information Ratio
Mean	3.43%	7.46%	0.79	−0.95%	2.66%	−0.34
Std. Dev.	2.04	5.80	1.08	0.35	1.36	0.35
10th Percentile	−3.74	2.46	−0.42	−1.99	1.58	−0.75
90th Percentile	10.87	13.84	1.87	0.18	3.56	0.07

Notes: The sample is 219 (96) credit hedge (mutual) funds for the period. Panel A (Panel B) shows credit hedge (mutual) funds. The green line in each graph shows a normal distribution with mean of zero and standard deviation equal to that of the average return distribution. The table below the graphs shows the full-sample distribution of annualized returns for the credit hedge (mutual) funds.

applied, 96 actively managed credit mutual funds remained.[4] The included funds represent 60% of the total assets managed by credit mutual funds in the Morningstar Direct database. The 86 excluded funds tended to be smaller (average AUM of $907 million compared with an average AUM of $1,361 million for the 96 included funds). Both total return and excess-of-benchmark return data were provided by Morningstar. Similar to our credit hedge fund data, these returns are net of all fees and are available at a monthly frequency from January 1997 through June 2018. The average credit mutual fund exists for 226 months.

We focus here on HY benchmarked credit mutual funds instead of investment-grade (IG) benchmarked managers because (1) the dedicated IG credit mutual funds are fewer than the HY funds and (2) those that are benchmarked to IG corporate indexes tend to hold a broader set of assets than simply corporate bonds, making any return- or holdings-based attribution inherently noisier. Past research also noted these important differences. For example, Choi and Kronlund (2018) examined both IG and HY funds and found that only 35% of holdings of IG benchmarked managers are corporate bonds, whereas for HY funds, this portion is closer to 75%. Cici and Gibson (2012) examined IG and HY funds and found a similar low level of corporate bond holdings for IG funds (average around 50%).

Table 1, Panel B, summarizes the performance (excess-of-benchmark returns) of long-only HY credit mutual funds in our sample. Unlike the credit hedge funds, over this time period, the average credit mutual fund reported annualized net-of-fee and net-of-benchmark returns of –0.82%. Panel B of Figure 1 reports the distribution of monthly net-of-fee and net-of-benchmark returns of our sample of 96 individual credit mutual funds. Whereas for credit hedge funds the distribution is shifted to the right of zero, the distribution for credit mutual funds is notably shifted to the left of zero. The average information ratio across the 96 funds is negative, –0.34. Our purpose in this article is to look beyond this headline result and assess whether credit mutual funds are providing adequate exposure to the traditional risk premiums embedded in the benchmark and/or exposure to well-compensated systematic factors.

For the holdings analysis of actively managed credit mutual funds, we obtained holdings data from the Lipper eMAXX corporate bond database. We did not need to be as strict with the selection criteria for credit funds as we were for the return analysis. For the return analysis, we required at least 80% of holdings to be in corporate bonds to avoid the returns of other assets contaminating our analysis of exposure to the credit market or systematic credit factors. For the holdings analysis, we included a broad set of credit funds and rescaled the weights on the corporate bond portion of the portfolio to sum to 1. We thus used a larger, less restrictive set of 146 mutual funds previously selected from Morningstar. We continued to require minimum corporate bond holdings of $50 million. We also added the 8 largest funds indexed to a BAML or Barclays benchmark that were in the Lipper eMAXX database but were not included in Morningstar. To select these 8 funds, we identified the largest 100 corporate bond funds by AUM (those holding more HY bonds than IG bonds) and removed all funds that (1) were already covered in our Morningstar sample, (2) were passive, and (3) did not have a stated corporate bond benchmark. Only 8 bond funds passed these filters. Our total sample was 154 funds. The Lipper eMAXX holdings data are available at a quarterly frequency from January 1998 through June 2018. The average fund in our sample had 36 quarters of holdings data and approximately $600 million held in corporate bonds, of which 96% were in US HY bonds.

Results

This section reports the detailed return analysis of credit hedge funds and of HY credit long-only funds. These discussions are followed by an analysis of the holdings of HY credit long-only funds.

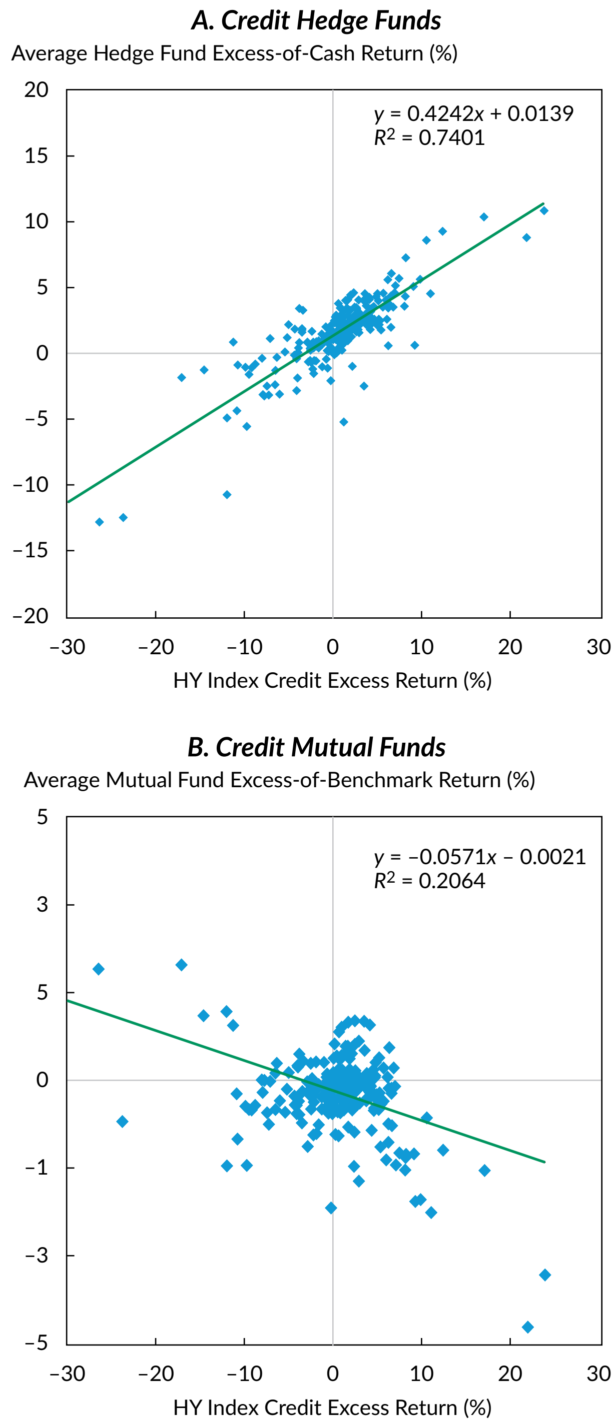
Detailed Return Analysis of Credit Hedge Funds.

We noted previously that the average credit hedge fund had positive net-of-cash returns and a Sharpe ratio of 0.79. But how much of that result is simply attributable to passive exposure to the credit market itself? Asness et al. (2001) made the point that hedge funds in general—and equity hedge funds in particular—contain a lot of passive exposure to the equity market. Little research, however, has documented how pervasive this phenomenon is for credit hedge funds. For our return decomposition analysis, we used overlapping three-month returns. This choice was deliberate to mitigate concerns of potential staleness in reported fund returns that might dampen any measured correlations or volatilities. Where we report *t*-statistics, we explicitly account for potential dependence introduced by overlapping three-month returns (by using the standard Newey–West correction). **Figure 2**, Panel A, is a scatterplot showing the contemporaneous correlation between the excess-of-cash (and net-of-fee) returns of an equally weighted basket of credit hedge funds and the credit excess returns of a diversified HY corporate bond index (both measured in overlapping three-month return windows). A positive relationship is clear—with a correlation of 86% (note the reported R^2). A potential limitation of looking at correlations with traditional risk premiums in a portfolio of individual credit hedge funds is that any true idiosyncratic returns may be diversified away. To address this issue, we show in Panel A of **Figure 3** the same correlation for each individual fund. The frequency histogram suggests that the vast majority of credit fund excess-of-cash returns are strongly positively correlated with the Credit risk premium. The median correlation is 0.61.

To explore this issue further, we extended the set of traditional risk premiums that we wished to examine to include (1) the Credit risk premium (the credit excess returns from the ICE BAML US High Yield Master II Index, ticker H0A0), (2) the Equity risk premium (the excess-of-cash returns to the S&P 500 Index), and (3) the Treasury risk premium (the excess-of-cash returns from the ICE BAML US Treasuries 7–10 Years Index, ticker G4O2). **Table 2** reports annualized returns, Sharpe ratios, and correlations for these three traditional risk premiums for our sample. Panel A shows that all three traditional risk premiums have positive risk-adjusted returns. Panel B shows that the Credit and Equity risk premiums are strongly positively correlated and that both are negatively correlated with the Treasury risk premium in this time period.

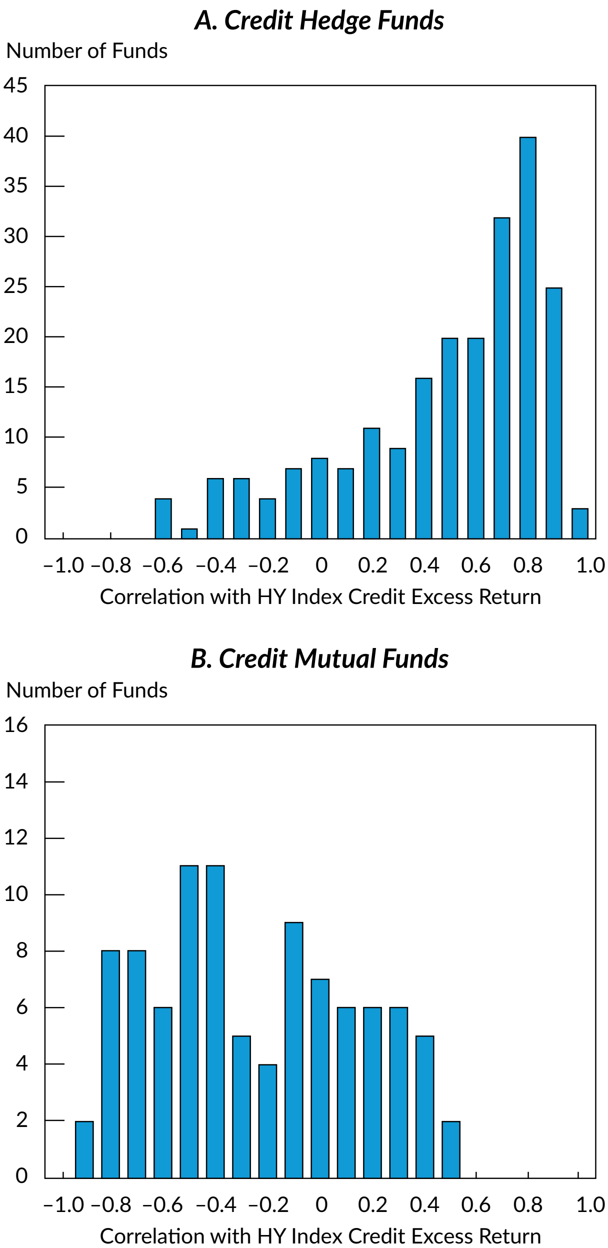
Table 3 reports the results of regressing net-of-fee and net-of-cash credit hedge fund returns on the three traditional risk premiums (for overlapping three-month returns). Panel A reports results for individual credit hedge funds from the full sample of available overlapping three-month returns for each fund. Across our 219 credit hedge funds, we found that the average (median) hedge fund has 48% (49%) of its return variation explained by passive exposure to traditional market risk premiums. Clearly, a hidden beta is packaged as alpha within the set of credit hedge funds. Panel B reports regression results for the HFRI Relative Value: Fixed Income-Corporate Index category returns against the market risk premiums. Passive exposure to the Credit risk premium alone explains 75% of the variation in credit hedge fund category returns, and all three traditional

Figure 2. Aggregate Credit Exposure of Actively Managed Credit Funds, January 1997–June 2018



Notes: The overlapping three-month equal-weighted average excess-of-cash (excess-of-benchmark) returns for our sample of credit hedge (mutual) funds and the Credit risk premium were measured as the credit excess returns of the ICE BAML US High Yield Master II Index. The sample includes 219 (96) credit hedge (mutual) funds.

Figure 3. Credit Exposure across Individual Actively Managed Credit Funds, January 1997–June 2018



Notes: The frequency histograms report contemporaneous correlations for each credit hedge (mutual) fund. Our sample covers 219 (96) credit hedge (mutual) funds. Returns are for overlapping three-month periods.

risk premiums combined explain 76% of the return variation. Notably, in the last specification reported in Panel B of Table 3, the intercept is 0.72 and is not significant [implying an alpha of 72 basis points (bps) annualized]. In results not reported in Table 3, across

Table 2. Traditional Market Risk Premiums, January 1997–June 2018

	Credit	Treasury	Equity
A. Summary statistics			
Annual return	2.79%	3.01%	6.32%
Annual volatility	11.88%	5.92%	15.63%
Sharpe ratio	0.24	0.51	0.40
B. Return correlation matrix for full sample			
Credit	1.00		
Treasury	−0.49	1.00	
Equity	0.75	−0.44	1.00

Notes: Treasury and Equity correspond to returns on, respectively, 10-year US Treasuries and the S&P 500 (both in excess of one-month Treasury returns). Credit is the return of the ICE BAML US High Yield Master II Index in excess of a Treasury portfolio with similar cash flows.

the set of 219 credit hedge funds, the mean (median) annualized regression intercept is 2.3 (1.3) with a corresponding *t*-statistic of 1.03 (0.94). Therefore, the annualized average excess-of-cash return of 3.43% reported in Figure 1 is primarily explained by passive exposure to traditional risk premiums. Note that the regression intercept (alpha) is likely to understate true alpha because the included explanatory variables are gross of fees. These return series are relatively cheap to access, however, for most institutional investors. What appeared at first glance to be impressive net-of-fee returns compared with a cash benchmark have been significantly reduced by subtracting returns associated with passive exposure to traditional risk premiums. To be fair, an attractive risk-adjusted return still exists across the set of credit hedge funds. To make that clear, **Figure 4**, Panel A, shows the distribution of annualized net-of-fee and net-of-traditional-risk-premiums returns across the set of 219 credit hedge funds. What is striking about this graph is the large shift to the left in the distribution. Indeed, the average information ratio for the credit hedge funds is 0.48, and it is significantly smaller than the simple Sharpe ratio of 0.79 reported in Figure 1.

Our next objective was to assess whether credit hedge funds, both in aggregate and individually, provide exposure to well-compensated systematic investment themes. For this exercise, we first captured passive exposures to traditional risk premiums (via the overlapping three-month return regression

Table 3. Traditional Market Risk Premiums in Credit Fund Returns, January 1997–June 2018 (*t*-statistics in parentheses)

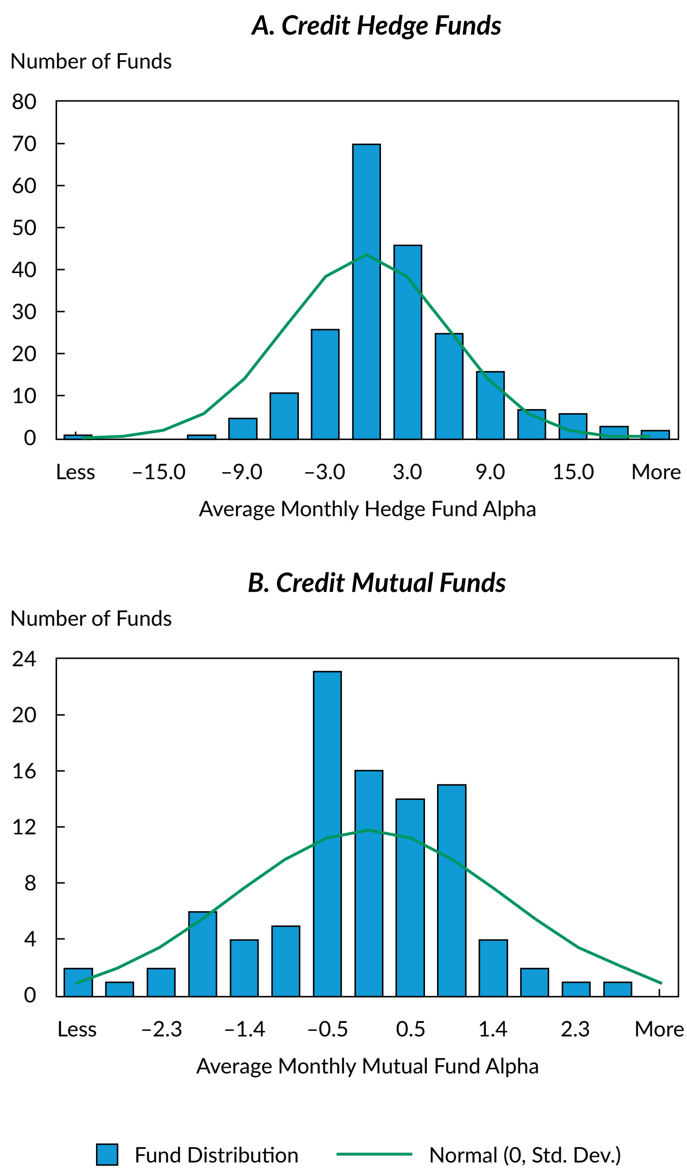
	Hedge Funds	Mutual Funds
A. Explanatory power of benchmarks for hedge funds and mutual funds		
Average	48%	91%
Median	49	92
75th percentile	70	95
Maximum	96%	98%

	Credit	Equity	Treasury	All
B. Explanatory power of benchmarks for HFRI Relative Value: Fixed Income-Corporate Index				
Credit	0.55			0.54
	(11.2)			(6.9)
Equity		0.33		0.04
		(5.3)		(0.6)
Treasury			−0.48	0.10
			(−3.1)	(1.4)
Intercept (annual)	1.21	0.67	4.20	0.72
	(1.3)	(0.5)	(2.7)	(0.9)
R^2	75%	46%	14%	76%

	Credit	Equity	Treasury	All
C. Explanatory power of benchmarks for credit mutual fund index				
Credit	0.75			0.84
	(26.6)			(35.8)
Equity		0.43		0.03
		(7.0)		(2.5)
Treasury			−0.40	0.46
			(−2.3)	(14.4)
Intercept (annual)	1.38	0.76	4.68	−0.40
	(2.3)	(0.5)	(2.4)	(−1.3)
R^2	91%	51%	6%	98%

Notes: In Panel A, for both credit hedge funds and mutual funds, the benchmark is specific to each of 219 hedge funds, estimated as a linear combination of equity, credit, and Treasury market returns with weights determined by a full-sample regression of fund returns on those three variables. In Panels B and C, Treasury is the excess-of-cash return on the ICE BAML US Treasuries 7–10 Years Index, Equity is the excess-of-cash return on the S&P 500, and Credit is the credit excess return of the ICE BAML US High Yield Master II Index.

Figure 4. Distribution of Alpha across Individual Actively Managed Credit Funds, January 1997–June 2018



	Credit Hedge Funds			Credit Mutual Funds		
	Excess Return	Volatility	Information Ratio	Active Return	Volatility	Information Ratio
Mean	2.26%	5.87%	0.48	−0.21%	2.68%	0.00
Std. Dev.	2.97	4.81	1.16	0.73	1.71	0.43
10th Percentile	−3.75	1.67	−0.79	−1.70	1.43	−0.55
90th Percentile	9.41	10.84	1.87	0.97	3.27	0.58

Notes: Passive exposures to traditional market risk premiums were removed individually for each fund by using a full-sample regression of overlapping three-month net-of-fee and excess-of-cash returns on the Credit risk premium (Credit), Equity risk premium (Equity), and Treasury risk premium (Treasury). The sample is 219 (96) credit hedge (mutual) funds. The green line in each panel shows a normal distribution with mean of zero and standard deviation equal to that of the average return distribution. The table on the bottom shows the full-sample distributions of annualized alphas.

described previously) and removed this component from the returns of each credit hedge fund.

The remaining alpha was then regressed on the returns of long–short factor portfolios for the following systematic investment themes: value, momentum, carry, and defensive. We used the same measures as in prior research (see, e.g., Israel et al. 2018). Full descriptions of the measures are given in Appendix A. Previous research (e.g., Israel et al.) showed that these systematic themes deliver positive risk-adjusted returns without providing exposure to traditional market risk premiums. In **Table 4**, Panels A, B, and C report the results of this regression as an average across credit hedge funds. In these three panels, only limited evidence is provided that credit hedge fund returns are associated with systematic investment themes, either individually or jointly. Collectively, the four systematic investment themes explain between 7% and 12% of the variation in aggregate credit hedge fund excess returns.

A limitation of the previous analysis of aggregate credit hedge fund returns is that the performance of individual credit hedge funds that provided minimal exposure to traditional risk premiums and/or maximal exposure to systematic investment themes could be "drowned out" by the average manager. **Figure 5**, Panel A, therefore, displays the distribution

Table 4. Credit Fund Index Exposure to Characteristics, January 1997–June 2018 (*t*-statistics in parentheses)

	Value	Momentum	Carry	Defensive	All
A. Credit hedge fund HFRI market-adjusted return					
Value	0.06				–0.06
	(1.4)				(–0.6)
Momentum		–0.05			0.05
		(–0.8)			(0.6)
Carry			0.08		0.22
			(1.6)		(2.0)
Defensive				0.13	0.21
				(1.0)	(1.7)
Intercept (annual)	0.36	1.10	0.72	0.18	–0.25
	(0.4)	(1.4)	(0.9)	(0.3)	(–0.2)
R^2	1.39%	0.88%	2.96%	3.70%	11.66%
B. Market-adjusted return for credit hedge fund US-centric corporate index (equal weighted)					
Value	0.06				0.09
	(1.5)				(1.2)
Momentum		0.01			0.08
		(0.3)			(1.3)
Carry			0.03		0.06
			(0.6)		(0.6)
Defensive				0.08	0.11
				(1.2)	(1.7)
Intercept (annual)	2.34	2.58	2.70	2.34	1.04
	(3.2)	(4.8)	(4.2)	(4.1)	(1.7)
R^2	2.40%	0.15%	0.47%	2.81%	8.85%

(continued)

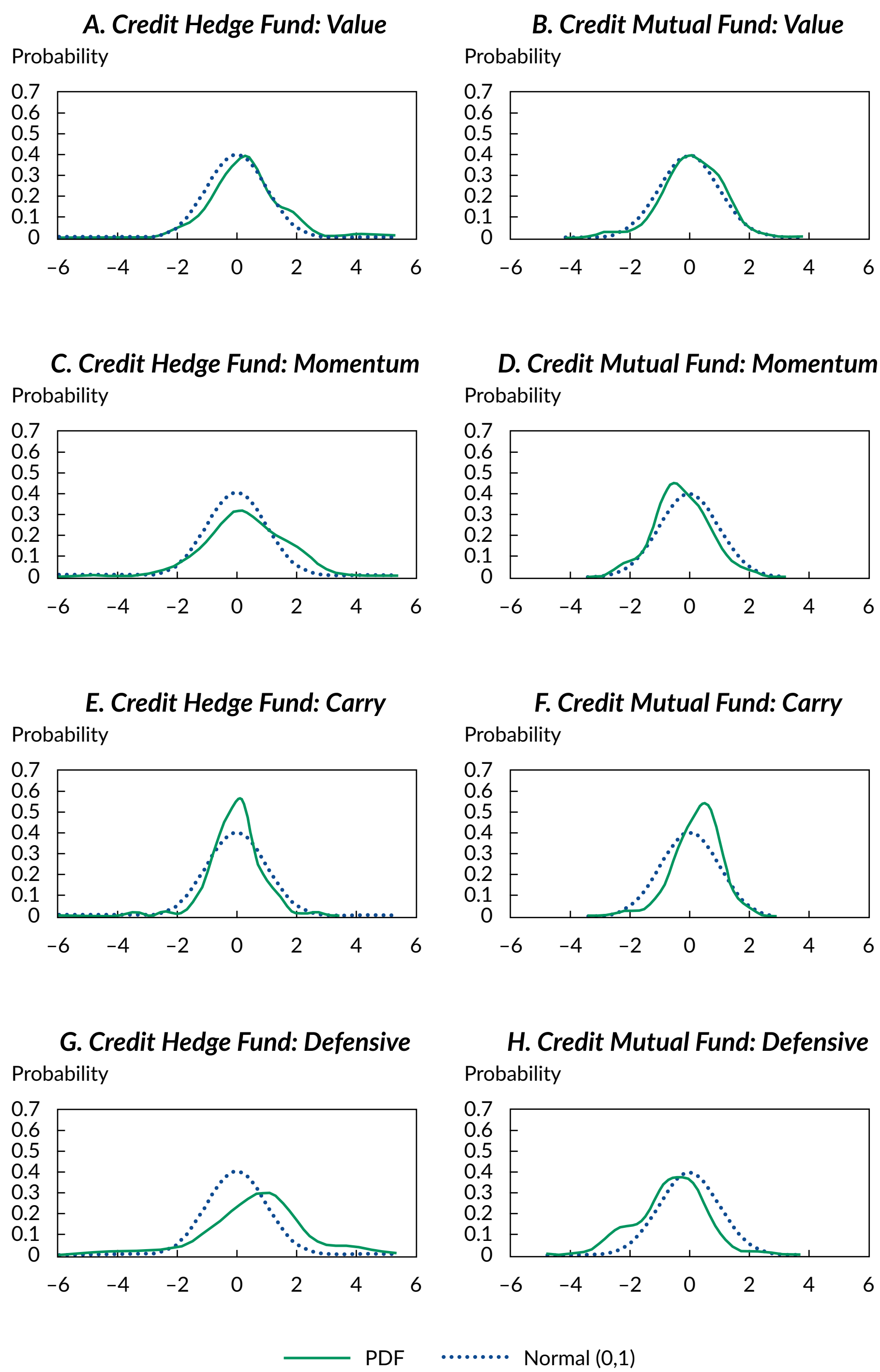
Table 4. Credit Fund Index Exposure to Characteristics, January 1997–June 2018 (*t*-statistics in parentheses) (continued)

	Value	Momentum	Carry	Defensive	All
C. Credit hedge fund US-centric corporate index market-adjusted return (asset weighted)					
Value	0.01				0.03
	(0.2)				(0.6)
Momentum		0.02			0.04
		(0.7)			(0.6)
Carry			−0.01		0.02
			(−0.3)		(0.3)
Defensive				0.11	0.12
				(1.5)	(1.9)
Intercept (annual)	1.33	1.20	1.39	0.91	0.35
	(1.9)	(1.9)	(2.3)	(1.8)	(0.4)
R^2	0.10%	0.45%	0.16%	5.81%	7.04%
D. Credit mutual fund index market-adjusted return					
Value	0.01				−0.01
	(0.4)				(−0.2)
Momentum		−0.02			−0.01
		(−0.6)			(−0.3)
Carry			0.02		0.01
			(0.7)		(0.4)
Defensive				−0.02	−0.02
				(−0.5)	(−0.3)
Intercept (annual)	−0.47	−0.25	−0.40	−0.29	−0.21
	(−1.4)	(−0.8)	(−1.4)	(−1.2)	(−0.5)
R^2	0.32%	0.83%	0.99%	0.86%	1.50%

Notes: The index used in Panel A is the HFRI Relative Value: Fixed Income-Corporate Index. The index used in Panel B is an equal-weighted average of our 219 US-centric credit hedge funds from the HFRI. The index used in Panel C is an asset-weighted average of our 219 US-centric credit hedge funds from the HFRI. The index used in Panel D is an equal-weighted average of the 96 corporate bond mutual funds in our Morningstar sample. Market-adjusted return is the difference between the excess-of-cash return of each credit fund and a market-hedging portfolio. The hedging portfolio is a linear combination of Equity, Credit, and Treasury market returns, where the weight was determined by a full-sample regression of fund returns on those three market returns.

of *t*-statistics across our set of 219 credit hedge funds. The *t*-statistic for a given systematic exposure was estimated separately by using the full sample of returns for each credit hedge fund. The dotted line is a normal distribution, and the solid line is the empirical distribution. The probability densities of the *t*-statistics are similar to those for the aggregate credit hedge fund results in Table 4; only marginal evidence is seen of credit hedge funds tilting toward the value, momentum, and defensive themes. In unreported results, we also tested whether the distribution of *t*-statistics across managers is different from the standard normal (which is what we would expect if their true exposure was zero and sample sizes were not an issue). We could reject the null hypothesis for value, momentum, and defensive, but

Figure 5. Systematic Factor Exposures across Individual Actively Managed Credit Funds, January 1997–June 2018



Notes: PDF is the probability density function. Empirical densities are given of the cross-sectional distribution of *t*-statistics of the slope coefficient from regressions of individual fund alphas on long–short portfolios targeting exposures to systematic investment themes. Our sample is 219 (96) credit hedge (mutual) funds. Fund-specific alphas or market-adjusted returns are the difference between the excess-of-cash return of each credit fund and a market-hedging portfolio. The hedging portfolio is a linear combination of Equity, Credit, and Treasury market returns, where the weight was determined by a full-sample regression of fund returns on those three market returns.

the economic magnitude of these tilts is small. We interpret the results in Table 4 and Figure 5 as showing that credit hedge funds, in aggregate and individually, have only limited exposure to these themes.

Detailed Return Analysis of HY Credit Long-Only Funds. Our methodology for analyzing actively managed credit long-only mutual funds largely followed that for the credit hedge funds. We continued to use overlapping three-month returns to mitigate issues related to stale pricing and return measurement. First, we examined the exposure of the long-only funds to the Credit risk premium. Unlike a hedge fund, however, a long-only mutual fund is meant to provide exposure to the risk premium embedded in the benchmark. So, Table 3, Panel A, naturally shows that the average credit mutual fund has 91% of its return variation attributable to the Credit risk premium. But to what extent does that result reflect a full capture of the Credit risk premium? Figure 2, Panel B, is a scatterplot showing the contemporaneous correlation between the excess-of-benchmark (and net-of-fee) returns of an equally weighted basket of actively managed credit mutual funds and the credit excess returns of a diversified HY corporate bond index (both measured by using overlapping three-month returns). In contrast to the credit hedge fund results shown in Panel A of Figure 2, a negative correlation of 45% is clearly visible. Long-only active credit managers provide less credit exposure, on average, than their benchmarks. We achieved similar results by looking at individual credit mutual funds in Panel B of Figure 3. The frequency histogram suggests that the vast majority of credit mutual fund excess-of-benchmark returns are negatively correlated with the Credit risk premium. The median correlation is –0.3. An important aspect is that these correlations were based on the full sample of returns and hence reflect a strategic allocation choice. We are not talking about temporal variation in the exposure to credit markets that may coincide with market performance. Therefore, this static (strategic) underexposure to credit markets may, in part, explain the negative net-of-fee returns documented in Panel B of Figure 1. Over the 1997–2018 period, the credit excess return from a broad diversified HY benchmark was nearly 3% annualized. Failing to capture that return fully in a portfolio created a meaningful headwind for the manager when returns were compared with those of the benchmark.

Panel C of Table 3 reports regression results documenting the extent to which traditional market risk premiums explain aggregate credit mutual fund returns. Similar to what we did for the hedge funds, we regressed net-of-fee and excess-of-cash aggregate credit mutual fund returns on the three traditional risk premiums by using overlapping three-month returns. Panel C of Table 3 shows that traditional market risk premiums, primarily the Credit risk premium, explain more than 90% of the variation of aggregate credit mutual fund returns. The regression coefficient of 0.75 suggests a lower beta than that implied in Panel B of Figure 2. The reason for this difference is that in Panel B of Figure 2, excess-of-benchmark returns were computed relative to the stated benchmark for each mutual fund. Given that some funds had safer (BB/B) HY benchmarks than others, the regression in Panel C of Table 3 included a broad HY index that contained riskier bonds. The result is a lower estimated aggregate credit mutual fund beta.

To visualize the impact of controlling for passive beta, Figure 4, Panel B, illustrates the annualized net-of-fee, excess-of-cash, and excess-of-passive-beta (i.e., alpha) returns across our 96 individual credit mutual funds. In contrast to the credit hedge fund results, the return distribution here is shifted slightly to the right. The reason is that individual credit mutual funds had less than unit exposure to the Credit risk premium, which delivered a robust risk-adjusted return in our sample period. Note that the average information ratio across funds improved to zero (Figure 4) from –0.34 (Figure 1) and the average annualized excess-of-benchmark return of –0.95% improved to –0.21%.

We next examined whether credit mutual funds, both in aggregate and individually, provide exposure to well-compensated systematic investment themes. We ran the same overlapping three-month regression analyses as described in the section “Detailed Return Analysis of Credit Hedge Funds.” We first measured the alpha for each credit mutual fund by regressing its net-of-fee and net-of-cash return on the three traditional risk premiums; we removed this passive beta component of returns from each credit mutual fund. Panel D of Table 4 reports results for an equal-weighted aggregate of credit mutual funds. It contains no evidence of significant exposure in these funds—either individually or in aggregate—to any of the systematic investment themes. In aggregate, the four themes explain only 2% of the variation in aggregate credit mutual fund excess returns.

Turning to the 96 individual credit mutual funds, Panels B, D, F, and H of Figure 5 show the distribution of *t*-statistics reflecting exposure to each individual theme. The results here are similar to the aggregate result—little evidence of individual credit mutual funds having exposure to the systematic investment themes. Unreported Kolmogorov–Smirnov tests rejected the null hypothesis that the empirical *t*-statistic distribution follows a standard normal only for carry, but again the economic magnitude of this tilt is small. We interpret the results in Table 4 and Figure 5 as showing that credit mutual funds, in aggregate and individually, have virtually no exposure to systematic investment themes.

Holdings Analysis of HY Credit Long-Only Funds.

Our final, and arguably most powerful, analysis to detect exposure to systematic investment themes entailed examining bond-level portfolio holdings data for a broad set of credit mutual funds. For this analysis, we used quarterly reports from Lipper eMAXX for our 154 funds, which yielded a sample of 5,536 fund-quarter reports for the 1998–2018 time period. We computed active weights for each fund-quarter by finding the difference between the weight of a given corporate bond in the fund and the weight of that bond in the respective fund benchmark. We then used these active weights to assess exposure to systematic investment themes.

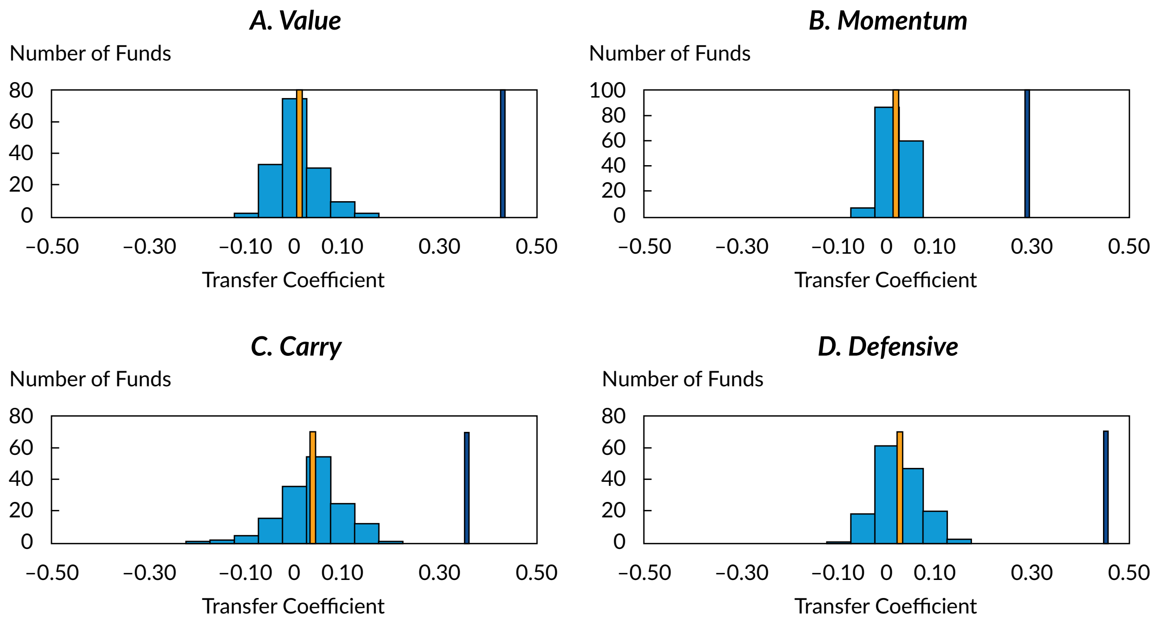
For this exercise, we measured each bond's attractiveness across the four systematic investment themes. At the end of each filing quarter, we assigned all constituent bonds in the ICE BAML US High Yield Master II Index a standardized score across the four systematic themes. We then computed for each fund-quarter the correlation between active weights and this standardized measure. This correlation summary statistic captures the extent to which a credit fund's overweights were consistent with a given systematic investment theme. The correlation can also be interpreted as a transfer coefficient (TC) when the asset-by-asset covariance matrix is proportional to an identity matrix (see, e.g., Clarke, de Silva, and Thorley 2002). Henceforth, we will refer to this cross-sectional correlation as TC for simplicity.

A negative TC for a certain style means that the fund is shorting that style, a zero TC means that the fund has no exposure to the style, and a TC of 1 means that the fund is maximally exposed to the style. As discussed in Clarke et al. (2002), a TC of 1 is highly unlikely because even if the manager uses a certain style as its sole measure of alpha, portfolio constraints (such as no shorting, leverage limits, and transaction costs) can drive the TC below 1. To provide a more realistic benchmark, we also included in our analysis a hypothetical long-only fund that explicitly targeted exposures to a risk-balanced combination of the four systematic investment themes. This hypothetical long-only fund is included in the histograms in **Figure 6**. The full details of the linear program underpinning this long-only portfolio is described in Israel et al. (2018), and the most pertinent details are summarized in Appendix B.

Panel A of **Table 5** provides the global average TC across all funds and quarters. The average TC across all four systematic investment themes is positive. Note that, although statistically different from zero, however, the TCs are economically close to zero. In Panel B, we saw a similar result when we regressed active weights directly on the standardized measures. This regression was run for each fund-quarter and then averaged across fund-quarters. Again, although a directionally positive and statistically significant association is visible for momentum, carry, and defensive, the magnitude of these coefficients suggests tiny average active weight exposures. For example, a 1 standard deviation increase in the attractiveness of a corporate bond based on our standardized measure of carry is associated with a 1.4 bp larger active weight on that corporate bond. The average R^2 from the regressions reported in Panel B of Table 5 is 2%, and the maximum is 6%. Even if we consider systematic exposures jointly, we see little evidence that the average credit manager targets these systematic exposures. This result may not be surprising if we assume that the set of actively managed credit mutual funds is representative of the market. (As of the end of our sample period, about 25% of the outstanding HY corporate debt was held by mutual funds.) Investing is a zero-sum game, so the average TC should be close to zero.

What is most interesting is the distribution of TCs across credit mutual funds. We show the relevant frequency histograms in Figure 6. The vertical orange line corresponds to the average value shown in Panel A of Table 5. It is striking how concentrated the distribution of TCs is around zero for all four systematic investment themes. The largest TCs among the various funds are around 0.15. The TCs for the hypothetical systematic portfolios (the blue vertical lines) are far from 1 but much larger than the typical active credit

Figure 6. Average Correlation of Individual Actively Managed Mutual Funds with Systematic Investment Themes, January 1997–June 2018



Notes: The figure shows the full-sample average correlations of each credit mutual fund with systematic investment themes. The sample consists of 154 high-yield mutual funds. The orange line in each graph shows the cross-sectional average correlation, and the blue line shows the average correlation for a hypothetical long-only portfolio designed to maximize exposure to the four systematic investment themes. The TC for a given fund-quarter was computed as the cross-sectional correlation between fund active weights and standardized measures representative of each investment theme.

fund, showing that active current managers have little exposure to systematic investment themes.

To help make that point clear, **Figure 7** contains an alternative visualization of the differences between exposures to systematic investment themes for actively managed credit mutual funds and the hypothetical systematic portfolio. To construct Figure 7, we assigned to every constituent bond in the HY index a score that describes its combined attractiveness vis-à-vis the four systematic themes. We then sorted the constituent bonds on this composite score from most to least attractive and assigned them to quartiles. For each fund-quarter, we then summed up the portfolio weights across the four attractiveness quartiles. The bar on the left in Figure 7 is the average across all credit mutual funds, and the bar on the right is for the hypothetical systematic portfolio.

Consistent with the analysis in Figure 6, Figure 7 provides no evidence of portfolio tilts toward well-compensated systematic investment themes in these actively managed credit funds. This statement is not to say that actively managed credit funds take no risk or that they are ignorant about how active risk is taken. Rather, we simply suggest that systematic investment approaches are different from traditional discretionary ones. This difference is important because it is a potential source of diversification benefit. What is also true of the hypothetical long-only systematic portfolio is that it is designed to deliver a beta of 1 with respect to the HY benchmark, unlike the actively managed credit funds, which, as we showed earlier, had too little exposure to the benchmark itself. This combination of a full capture of the Credit risk premium and a set of systematic exposures that do not contain exposure to traditional risk premiums is a potentially powerful complement to an investor's portfolio.

General Discussion of Systematic Credit Investing

The purpose of this section is to help define what "systematic credit investing" is—and what it is not. The empirical analysis in this article used relatively

Table 5. Analysis of HY Mutual Fund Holdings, January 1997–June 2018 (*t*-statistics in parentheses)

	Correlation (TC)
A. Active weight correlation of mutual funds with systematic investment themes	
Value	0.01
	(2.6)
Momentum	0.02
	(10.1)
Carry	0.04
	(6.9)
Defensive	0.03
	(6.7)
	Dependent Variable: Active Weight (bps)
B. Average loadings from regressions of mutual fund holdings on systematic investment themes	
Value	–0.19
	(–0.9)
Momentum	0.47
	(5.2)
Carry	1.42
	(8.6)
Defensive	0.93
	(13.8)

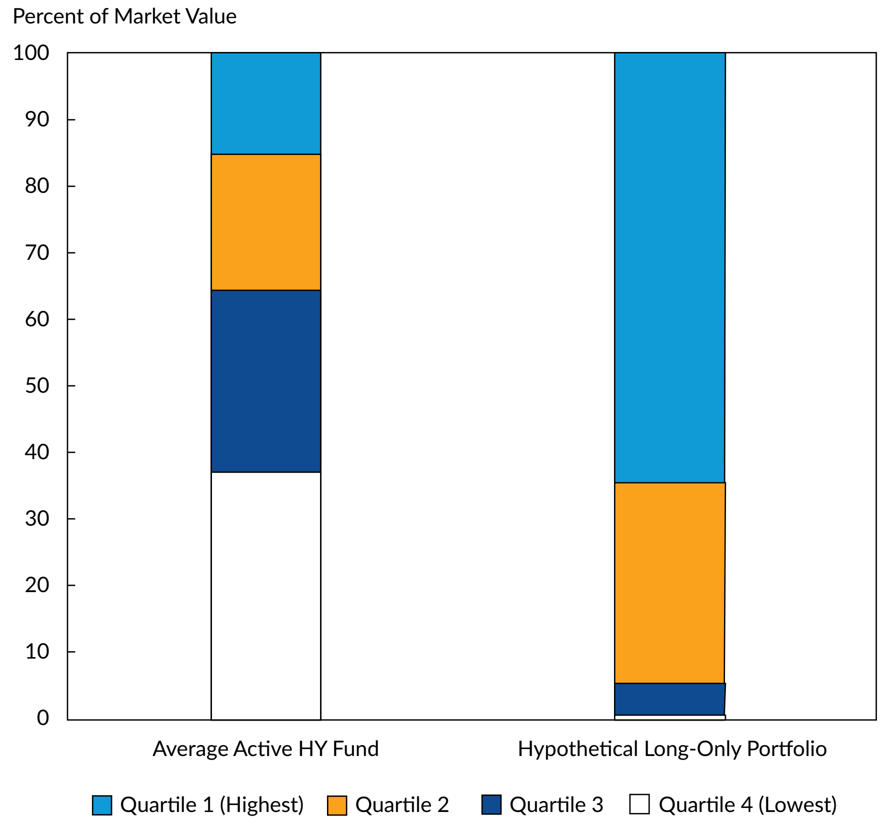
Notes: Distribution of quantities of interest are given for 5,536 mutual fund reports by 154 unique HY credit mutual funds. The 154 funds had portfolio holding information contained in the Lipper eMAXX database, and these funds have an explicit high-yield benchmark belonging to one of the two most popular benchmark providers: BAML and Barclays. Active weights are weights in excess of the respective benchmark for each fund. Note that *t*-statistics of the averages are clustered at the fund and quarter levels.

simple measures and simple portfolio construction techniques. These choices help ensure the transparency and full replicability of our results. Generally, however, systematic investing need not be limited to simple measures. Indeed, systematic credit investing is a fundamentally driven, yet systematically implemented, approach to portfolio construction. Good fundamental analysts are not going to limit themselves to the simplest financial statement ratios to assess default risk, nor should a systematic approach be limited. Systematic investing need not imply a "smart beta" approach.

Because most academic research has been conducted on cross-sectional drivers of equity returns, scores of investment products have been designed to harvest these return drivers (typically described as "factors," "styles," or "smart beta"). To the extent that measures are well known and understood (and there is general agreement as to their implementation), to label systematic harvesting of the return drivers as factor- or style-based investing is fine. For credit markets, however, we believe that to label systematic harvesting of recently documented cross-sectional drivers of credit excess returns as factor or style investing is premature. First, few asset managers have a truly systematic approach in credit markets (indeed, such is the point of this article). Second, we have not reached a clear agreement on how various attributes should be measured (e.g., how to model default). Third, the credit markets are far more challenging than the equity markets for trading or for building a portfolio that systematically targets exposures to desirable attributes. Indeed, our analysis suggests that even with simple measures of systematic themes (value, momentum, carry, and defensive), little of the active credit fund manager returns or holdings can be explained with a systematic approach. For equity funds, in contrast, academic research examining style exposures goes as far back as Brown and Goetzmann (1997); Carhart (1997); and Chan, Chen, and Lakonishok (2002). These authors generally found that simple factors have significant explanatory power for both equity fund returns and holdings, especially when looking at equity funds in the standard Morningstar categories. This difference between credit and equity funds is partly a result of the general acceptance and broad use of equity style measures by fund managers as well as by entities that create categories for equity funds, such as Morningstar. In the future, we expect to see increasing acceptance and use of systematic investing approaches in credit markets; therefore, our tests might produce different results in future years.

For this article, we used measures of value, momentum, carry, and defensive factors as defined in Israel et al. (2018). Although this approach has the primary benefits of transparency and replicability, it comes with a potential cost in that it is naturally limited and may not reflect the depth of analysis (measures and portfolio construction choices) being applied in actual (proprietary) portfolios.

Figure 7. Average Credit Mutual Fund Holdings Divided into Quartiles Based on Systematic Investment Theme Scores, as of 30 June 2018



Notes: Quartiles are based on combined scores across all four systematic themes (value, momentum, carry, and defensive). The hypothetical long-only HY portfolio was designed to maximize exposure to the four systematic investment themes.

Conclusion

We undertook a comprehensive analysis of the behavior of actively managed credit hedge funds and mutual funds. We asked a simple question: Do actively managed credit funds deliver active returns that are uncorrelated with traditional market risk premiums? We found limited evidence in support of this idea.

First, credit hedge funds provide meaningful exposure to the Credit risk premium, and that exposure may be more than the funds' investors expect (around half of the return variation is explained by credit beta). Just as equity hedge funds have been shown to have significant passive exposure to the equity market, we found a strong footprint of passive exposure to credit beta in credit hedge funds. Credit mutual funds, in contrast, provide too little exposure to the Credit risk premium. They are, in effect, creating a headwind for themselves. Given the existence of a risk premium from exposure to credit-sensitive assets (see, e.g., Asvanunt and Richardson 2017), this headwind may help explain the negative net-of-fee returns for credit mutual funds.

Second, despite evidence of (1) a robust relationship between well-known systematic investment themes (i.e., value, momentum, carry, and defensive) and corporate bond excess returns and (2) the feasibility of implementing exposures to these themes, individual credit funds are only minimally exposed to themes that generate meaningfully positive risk-adjusted returns. Investors in actively managed credit funds should be aware of the beta they are exposed to (too much in credit hedge funds and too little in credit mutual funds) and the lack of exposure to systematic investment themes. Our results suggest that credit investors may have an opportunity to gain exposure to well-compensated investment themes that will diversify their holdings and complement their exposure to traditional market risk premiums.

Appendix A. Variable Definitions and Details

Variable	Definition
Treasury	Excess returns to long-term government bonds, measured as the difference between total returns on the ICE BAML US Treasuries 7–10 Years Index (ticker G4O2) and one-month US T-bills, sampled at a rolling quarterly frequency.
Credit	Excess returns to corporate bonds, measured as the difference between the return of the ICE BAML US High Yield Master II Index (ticker H0A0) and a portfolio of US T-bonds with similar cash flows, sampled at a rolling quarterly frequency.
Equity	Excess returns to the S&P 500 Index, measured as the difference between total returns to the S&P 500 and one-month US T-bills, sampled at a rolling quarterly frequency.
Active weight	Bond weight in excess of the stated benchmark for a given mutual fund.
Correlation (transfer coefficient)	The cross-sectional correlation of fund manager active weights and standardized scores across the respective systematic investment themes. The correlation was measured for each fund-quarter and can be averaged across both funds and time.
Market-adjusted returns	Returns in excess of traditional market risk premiums, measured as the difference between the returns of a credit fund and a fund-specific market-hedging portfolio (MHP). The MHP was determined by a full-sample regression of a credit fund's excess-of-cash return on the returns of traditional market risk premiums (Credit, Equity, and Treasury)—all sampled at a rolling quarterly frequency.
Carry	A long–short portfolio targeting exposure to the carry investment theme, measured by option-adjusted spread (OAS) as reported in the BAML bond database. This portfolio was long (short) the top (bottom) 20% of bonds each month, and returns were value weighted. Reported returns are credit excess returns.
Value	A long–short portfolio targeting exposure to the value investment theme. Value was measured by two fair value regressions: first, as the residual from a cross-sectional regression of the log of OAS on the log of duration, rating, and bond excess return volatility (prior 12 months); second, as the residual from a cross-sectional regression of the log of OAS on the log of the default probability implied by a structural model (for details, see Shumway 2001). To obtain a beta-neutral long–short value portfolio, we demeaned value within five *ex ante* beta quintiles, with beta being measured as spread duration times spread (DTS). This portfolio was long (short) the top (bottom) 20% of bonds each month, and returns were value weighted. Reported returns are credit excess returns.
Momentum	A long–short portfolio targeting exposure to the momentum investment theme. Momentum was measured by two price-based measures. The first was credit momentum from the most recent six-month cumulative corporate bond excess return. The second was equity momentum, defined as the most recent six-month cumulative issuer equity return. To obtain a beta-neutral long–short momentum portfolio, we demeaned momentum within five *ex ante* beta quintiles, with beta being measured as spread DTS. This portfolio was long (short) the top (bottom) 20% of bonds each month, and returns were value weighted. Reported returns are credit excess returns.
Defensive	A long–short portfolio targeting exposure to the defensive investment theme. Defensive was the combination of three measures: The first was market leverage, measured as the ratio of net debt (book debt + minority interest + preferred stocks – cash) to the sum of net debt and market capitalization. This measure used data available at the start of each month (assuming a six-month lag for the release of financial statement information). The defensive theme avoids issuers with high levels of leverage. The second measure was effective duration as reported in the BAML bond database. The defensive theme avoids issues with long duration. The third measure was gross profitability measured as gross profits scaled by average total assets. The defensive theme favors issuers with high levels of profitability. This portfolio was long (short) the top (bottom) 20% of bonds each month, and returns were value weighted. Reported returns are credit excess returns.

Appendix B. Long-Only Portfolio Implementation Details

To construct a long-only portfolio with maximal exposure to our selected systematic investment themes (value, momentum, carry, and defensive), we ran a linear program every month. The mathematical details of that linear program are given here. The objective was to select portfolio weights that were maximally correlated with a combined score (COMBO). COMBO is an equal-risk-weighted combination of the value, momentum, carry, and defensive characteristics for a given bond. The index used was the ICE BAML US High Yield Master II Index. We selected one representative bond per issuer (for details, see Israel et al. 2018). This process created a universe of 500–600 issuers each month that were both liquid and nondistressed. The constraints ensured that our portfolio of HY corporate bonds (1) was fully invested, (2) was long only (i.e., shorting was disallowed), (3) maintained a beta close to 1 via the spread duration and spread active weight deviations, and (4) was liquidity aware because of limited turnover and trading only in minimal sizes. In the notation below, $w_{i,t}$ is the optimal portfolio weight on bond i, $b_{i,t}$ is the weight of bond i on a cap-weighted portfolio of bonds in our universe, $r_{i,t}$ is the (cum-coupon) return of bond i at date t, $c_{i,t}$ is the coupon paid by bond i at date t as a percentage of the bond market value at date t – 1, and

$$w_{i,t}^{0} = \frac{\left(r_{i,t} - c_{i,t}\right)}{\sum_{j=1,\ldots,I} w_{j,t-1} \times \left(r_{j,t} - c_{j,t}\right)} w_{t,t-1}$$

is the weight bond i has on the portfolio at date t before any rebalancing.

$$\text{Maximize:} \sum_{i=1}^{I} w_{i,t} \cdot \text{COMBO}_i$$

subject to

$w_{i,t} \geq 0, \forall i$ (no shorting constraint)

$\left|w_{i,t} - b_{i,t}\right| \leq 0.25\%, \forall i$ (deviation from benchmark constraint)

$\sum_{i=1}^{I} w_{i,t} = 1$ (fully invested constraint)

$\sum_{i=1}^{I} \left|w_{i,t} - w_{i,t}^{0}\right| \leq 10\%$ (turnover constraint)

$\left|w_{i,t} - w_{i,t}^{0}\right| \times Nav_t \geq \$100{,}000, \forall i$, where $w_{i,t} - w_{i,t}^{0} \neq 0$ (minimum trade size constraint)

$\sum_{i=1}^{I} \left|\left(w_{i,t} - b_{i,t} \cdot \text{OAS}_{i,t}\right)\right| \leq 0.50\%$ (deviation from benchmark spread constraint)

$\sum_{i=1}^{I} \left|\left(w_{i,t} - b_{i,t} \cdot \text{Duration}_{i,t}\right)\right| \leq 0.50$ (deviation from benchmark duration constraint)

Editor's Note

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Notes

1. Prior research examining popular active fixed-income categories (e.g., global aggregate, US core, and core plus) has documented a pervasive overweight to credit markets. Specifically, AQR Capital Management (2018) showed that the excess-of-benchmark returns of global aggregate (core plus) managers have a 0.76 (0.95) correlation with the Credit risk premium. The key difference in the directionality of the weighting to the Credit risk premium lies in the risk of the respective benchmark. Unlike managers in other categories, HY managers cannot enhance returns by adding persistent out-of-benchmark exposures to risky credit. The lower beta for HY managers is probably attributable to a combination of (1) an inability to invest 100% in corporate bonds (remember that credit mutual funds are holding relatively less liquid assets inside a daily dealing vehicle and are, therefore, likely to hold cash in the fund) and (2) a possible desire to hold safer bonds and avoid defaults.

2. Of course, there is always the possibility of market timing, the subject of an extensive literature. Market timing is not the focus of this article, but we note that the persistence of beta mismatch in both credit hedge funds and credit mutual funds is inconsistent with an attempt to time the market, let alone a demonstration of skill in such timing.

3. Refer to Appendix A for definitions.

4. We also ran our analysis on a less restrictive sample—one without the filter of at least 80% of the portfolio being held in corporate bonds. This process created a sample of 146 actively managed credit funds. The broader set of funds captured 85% of the total assets managed by credit mutual funds in the Morningstar Direct database. Our results are similar for this alternative sample (i.e., too little beta and too little systematic exposure). We prefer the returns analysis to be based on the reduced sample, however, because it allows for cleaner inference. For example, in the larger sample, a failure to find evidence of systematic exposures could be criticized because the excluded assets (e.g., loans and equities) might distort any credit beta or systematic credit exposures from the corporate bond portion of the portfolio.

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