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In active equity funds, concentration matters. Active bond funds? It's complicated.

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- Academic and practitioner research has found a link between the number of securities in an actively managed equity fund and two performance parameters: systematic risk exposure and alpha potential. This paper explores whether the same relationship holds in an actively managed fixed income fund.

- We find that, all things being equal, the number of holdings in a fund has a statistically, but not an economically, significant link to systematic risk exposure. Furthermore, we find neither a statistically nor an economically significant link between the number of holdings in a fund and the fund's alpha.

- These findings contrast with those for equities. The contrast may result from differences in how investors can achieve issuer exposure through equities and the exposure delivered through fixed income securities. In equities, a single security captures the full risk of ownership in a single company. An issuer may sell a variety of fixed income securities, however, each with a different degree of exposure to the issuer's financial performance.

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Introduction

A large body of academic and practitioner research has explored the relationship between the number of holdings in an actively managed equity portfolio and two performance parameters: the degree to which portfolio performance is driven by systematic risk; and the portfolio's potential to generate alpha, or a return in excess of what can be explained by known risk factors.

This research has established a strong positive relationship between the number of securities and a portfolio's exposure to systematic risk. Foundational work by Graham (1949), Evans and Archer (1968), Fisher and Lorie (1970), Malkiel (1973), and Statman (2004) confirmed the stability of the relationship between the number of holdings and its effect on nonsystematic risk. Further, Sapp and Yan (2008) found that concentrated funds had statistically significantly less factor sensitivity to market, size, and momentum than diversified funds had. This research has also prompted a lively debate about whether concentrated or diversified actively managed equity funds are a better source of potential alpha.

We examine the same relationships in actively managed fixed income portfolios, a topic not extensively explored in the research literature.[1] Based on this nascent area of research, the question arises: Can the number of holdings in actively managed fixed income funds provide insight into the proportion of portfolio risk explained by systematic risk? And does it offer clues about a fund's potential to produce alpha?

We hypothesize that, as with equity portfolios, an actively managed fixed income portfolio's exposure to systematic risk increases with the number of holdings. To test this assumption, we obtain the number of holdings for a broad sample of actively managed, open-end U.S. taxable bond funds and determine whether the number of fund holdings is indeed positively correlated with the portion of total risk that is systematic.

The relationship of alpha to the number of holdings is less clear. In the absence of a generally applicable theory, we hypothesize that the dispersion of fund alphas increases as the number of holdings decreases. The rationale for this assumption is that a highly concentrated fund may happen to hold exactly those bonds that *outperform* over a given period. It is equally likely, however, that a concentrated fund may hold mainly those bonds that *underperform*.

We find from our analysis that, in contrast to equity funds, the relationship between the number of holdings in a fixed income fund and that fund's exposure to systematic risk is economically insignificant. And the number of holdings provides no insight into a fixed income fund's potential for alpha, again in contrast to equity funds.

We believe these findings may reflect differences in the issuer exposure delivered through equities and the exposure delivered through fixed income securities. In equities, a single security captures the full risk of ownership in a single company. An issuer may sell a variety of fixed income securities, however, each with a different degree of exposure to the issuer's financial performance. Some bonds may be callable, others not. Some may have short-term maturities, others long-term. The one-to-one relationship between security and issuer that prevails in the equity market fractures in the fixed income market.

Before we discuss our statistical approach, we will explain how we 1) select the underlying factors that predominantly explain bond returns and 2) measure systematic fixed income risk.

1 We leverage various natural language processing (NLP) techniques to ensure that we are not missing any potentially relevant research. We loaded a broad universe of potentially relevant academic research into a graph database and used NLP tokenization to extract a list of associated topics and entities for each paper. We curated this entity list to find papers that *explicitly* mention words associated with our topic of research interest. Finally, we leveraged Latent Dirichlet Allocation topic model vectors to identify thematically similar papers to our known universe and screened for papers that *implicitly* mention our topic of research interest. In doing so, we expanded our search far beyond basic keyword search or an ad hoc human review process.

Factor-based framework

In developing our fixed income factor framework, we leverage seminal work done by Fama and French (1993), who identified two factors that explained the majority of fixed income returns: maturity (Term) and default risk[2] (Credit). In addition, we leverage more recent work by Mladina and Germani (2019), who introduced the prepayment factor (Prepayment). Prepayment explains the risks associated with investing in bonds with prepayment features, such as mortgage-backed securities and, more broadly, callable bonds. Mladina and Germani found that the explanatory power of their model with the Term and Credit factors was improved when the Prepayment factor was included.

Additional academic literature and researchers sought to refine and improve these definitions and identified additional factors. Soe and Xie (2016) examined quantitative fixed income strategies in the investment-grade (IG) corporate bond market, attempting to capture value and low-volatility factor exposure. Roberts, Paradise, and Tidmore (2018) enhanced the Term factor, decoupled the default risk factor definitions into IG Credit and HY, or High-Yield, Credit factor, and introduced a currency factor, which applies to global active bond funds. Israel, Palhares, and Richardson (2018) found that carry, defensive, momentum, and value factor exposures explain corporate excess returns. Henke (2020) investigated factor investing in corporate bonds with single and multifactor strategies using value, equity momentum, size, carry, and quality.

While these examples are important contributions to the academic literature, for our purposes, Term, Credit, and Prepayment will capture the majority of the return variation of U.S. actively managed taxable bond funds. For example, additional factors cited in the literature specifically around carry, defensive, value, and momentum all have a common denominator of default risk exposure, which the Credit factor should incorporate.

R^2 as the proxy for systematic risk

De Jong and Fabozzi (2020) proposed a model for defining systematic risk within the corporate bond market, with the underlying bond factors stemming from duration, credit, and liquidity.[3] While we look at the broad U.S. active taxable fund universe, their study provides us with valuable insight.

Roll (1988) used the stock return synchronicity to measure R^2, the amount of return volatility that can be explained by market returns, and Amihud and Goyenko (2013) used R^2 to predict stock fund performance. These papers helped support our belief that we can apply R^2 as a measure of fixed income systematic risk. It is easily interpretable and can be derived from regressing the fund's return against our Term, Credit, and Prepayment factors. The higher the R^2, the stronger the association with systematic risk that reflects fixed income returns compared with firm-specific information. To empirically test our hypothesis about the relationship between the number of fund holdings and systematic risk, we will use R^2 as the dependent variable and the number of holdings as the independent variable.

2 We utilize an enhancement to the original Fama-French (1993) definition. The original paper used long-term investment-grade corporate credit returns in excess of long-term U.S. Treasury returns. We account for all credit excess return across the maturity curve.

3 The authors measured liquidity risk using bid-ask spreads at the individual corporate bond level. Our data set examines attributes at the fund level for the broad U.S. actively managed taxable bond universe compared with the individual corporate bond level, so we do not incorporate liquidity risk.

Data and methodology

We begin by capturing from Morningstar, Inc., the oldest share class of all U.S.-domiciled actively managed, open-end U.S. taxable bond funds in existence during the 180 months from 2005 through 2019, excluding funds-of-funds.

We group those funds by 11 Morningstar categories that best reflect broad investment strategies. These categories are: *U.S. Corporate, U.S. High-Yield, Short, Intermediate,* and *Long Government, Core, Core Plus, Multisector, Long-Term, Short,* and *Ultrashort*.

The number of holdings in a fund is obtained by taking the reported long and short positions for each month. Net holdings are then calculated by taking the difference between a fund's reported long holdings and short holdings for each month. We then calculated the average holdings over 36-month periods and took the natural log of each fund's holdings to adjust for the positive skew in the underlying data and linearize their relationship with the dependent variables. If there were no reported holdings (long or short), the fund was excluded from the sample.

In an effort to balance our long time frame against survivorship bias, we divided the 180 months into five nonoverlapping 36-month time intervals.

We then employed a two-step returns-based regression to estimate the relationship between both the number of holdings and R^2 and the number of holdings and alpha.

Two-step returns-based regression:

1. We regressed each fund's excess return over the risk-free rate on Term, Credit, and Prepayment factors (see Appendix A for factor definitions).

   Step 1: $R_{i,t} - rf_t = \gamma_0 + \gamma_1 \mathrm{Term}_{i,t} + \gamma_2 \mathrm{Credit}_{i,t} + \gamma_3 \mathrm{Prepay}_{i,t} + \varepsilon_{i,t}$

2. We regressed each fund's R^2 and alpha (calculated from Step 1) independently, on the natural log of fund holdings (Ln Holdings), controlling for fund size, asset manager fixed effects, and time effects.[4] (For a closer look at systematic risk, see "Risk decomposition of systematic risk" on page 7.)

   We then performed two additional steps to control for funds across the credit-quality and duration spectrum. We:

   a. Grouped the funds in our sample into three combined credit-quality buckets[5]: AAA/AA, A/BBB, and BB/B, based on the weighted average fund credit quality across all months in the sample 15-year time horizon. Each fund's R^2 and alpha were then regressed on Ln holdings for each credit-quality bucket.

   b. Grouped the funds in our sample into four combined duration buckets[6] based on average effective duration across all months in the sample 15-year time horizon: Ultrashort, Short, Intermediate, and Long. R^2 and alpha for each fund were then regressed on Ln holdings for each duration bucket.

Step 2: $$DV_{i,t} = \beta_0 + \beta_1 \ln(\#\mathrm{Hol}_i) + \beta_2(\mathrm{Size}_i) + \sum_{k=1}^{K} \beta_k \gamma_i + \sum_{x=1}^{4} \beta_i T_t + \varepsilon_{i,t}$$

Step 2a: $$DV_{i_G,t} = \beta_0 + \beta_1 \ln(\#\mathrm{Hol}_{i_G}) + \beta_2(\mathrm{Size}_{i_G}) + \sum_{k=1}^{K} \beta_k \gamma_{i_G} + \sum_{x=1}^{4} \beta_{i_G} T_t + \varepsilon_{i_G,t}$$

Step 2b: $$DV_{i_D,t} = \beta_0 + \beta_1 \ln(\#\mathrm{Hol}_{i_D}) + \beta_2(\mathrm{Size}_{i_D}) + \sum_{k=1}^{K} \beta_k \gamma_{i_D} + \sum_{x=1}^{4} \beta_{i_D} T_t + \varepsilon_{i_D,t}$$

R = excess monthly return over the risk-free rate, *DV* = dependent variable (= R^2, Alpha), *i* = fund, *t* = time, T_t = control for each three-year time period, *k* = control for individual asset manager, *G* = Specific credit-quality bucket (*AAA/AA, A/BBB, BB/B*), *D* = specific duration bucket (*Ultrashort, Short, Intermediate, Long*).

4 Each control variable is defined as follows: Fund size is calculated as the fund's assets under management (AUM) for the period, asset manager fixed effects is defined as a categorical control for each individual fund family, and time effects is defined as a categorical control for each 36-month time interval.

5 We created a weighted average credit score for each 36-month interval calculated as each fund's credit quality averaged across all months in the sample time horizon.

6 Using Morningstar data, we calculated each fund's average effective duration across all months in the sample time horizon to form each of the four duration buckets. These buckets were formed to control for the duration of a fund's holdings.

Figure 1 displays the descriptive statistics for all the relevant variables from our step 1 regressions for the full sample, as well as each credit-quality and duration subgroup.[7] We see that a majority of the funds in our sample fall within the A/BBB credit-quality bucket and the intermediate-duration bucket. We also observe that median holdings are greater for funds in the lower-credit-quality subgroups than for their higher-quality peers. We also note that average R^2 increases as we move across the lower-credit-quality spectrum groups and longer across the duration spectrum.

Figure 1. Descriptive statistics

A. Credit quality

	Number of funds	Median number of holdings	Excess return	R^2	Average factor loadings: Alpha	β_{term}	β_{credit}	β_{prepay}
Full sample	**1,940**	**288**	**4.20**	**0.72**	**0.04**	**0.23*****	**0.30*****	**0.16**
(t-stat)					**(0.32)**	**(8.41)**	**(6.17)**	**(0.57)**
AAA/AA	377	177	3.29	0.66	0.04	0.23***	0.01	0.24
					(0.29)	(10.26)	(0.44)	(0.95)
A/BBB	888	301	3.71	0.68	0.04	0.22***	0.16***	0.15
					(0.38)	(8.68)	(3.87)	(0.58)
BB/B	675	319	5.34	0.82	0.04	0.23***	0.64***	0.12
					(0.25)	(7.03)	(12.40)	(0.33)

B. Duration

	Number of funds	Median number of holdings	Excess return	R^2	Average factor loadings: Alpha	β_{term}	β_{credit}	β_{prepay}
Full sample	**1,940**	**288**	**4.20**	**0.72**	**0.04**	**0.23*****	**0.30*****	**0.16**
(t-stat)					**(0.32)**	**(8.41)**	**(6.17)**	**(0.57)**
Ultrashort	83	187	2.37	0.38	0.02	0.05***	0.10***	0.06
					(0.92)	(2.91)	(3.48)	(0.20)
Short	527	235	3.25	0.59	0.04	0.11***	0.23***	0.01
					(0.40)	(5.27)	(5.26)	(0.05)
Intermediate	1,244	327	4.62	0.80	0.05	0.27***	0.33***	0.22
					(0.27)	(9.61)	(6.65)	(0.81)
Long	86	231	5.57	0.83	0.00	0.46***	0.46***	0.22
					(–0.07)	(15.43)	(7.36)	(0.59)

*Statistically significant to 10%; **statistically significant to 5%; ***statistically significant to 1%.

Notes: A negative value in parentheses means it is a negative t-stat while a positive value in parentheses means it is a positive t-stat. The data presented are summary statistics for all each fund three-year period over the 15-year time horizon ended December 31, 2019. We group the funds into buckets based on average credit quality and average effective duration. We also display average factor loadings and R^2s from our three-factor step 1 regressions.

Sources: Morningstar and Bloomberg Barclays.

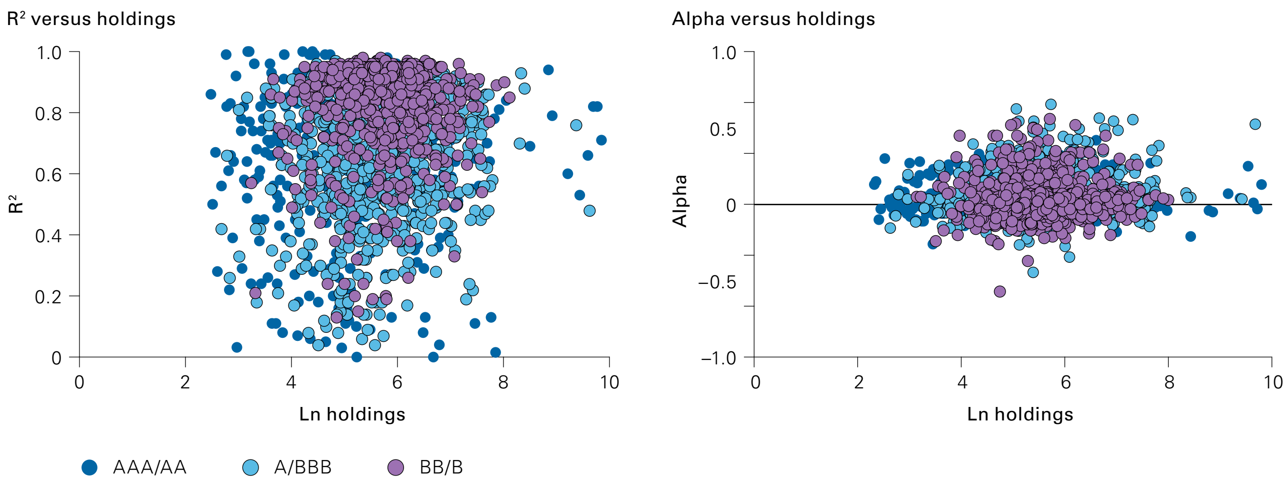
7 Appendix B also displays the descriptive statistics for each of the 11 Morningstar categories.

Fund scatterplots

Before we explore the relationship between the number of holdings and our measures of systematic risk and alpha, using statistical methods, we take our results populated from step 1 of our regression and depict these relationships graphically (see **Figure 2**).

The panel on the left does not suggest a clear link between the number of holdings and systematic risk or number of holdings and alpha, as displayed by the panel on the right—neither across the full sample nor within the three credit-quality groups. Additionally, in contrast to equities,[8] which have increased dispersion of alpha and returns as a fund reduces its holdings and becomes more concentrated, we don't see this with fixed income when looking at the full sample.[9]

Figure 2. Scatterplots of R^2/alpha and number of holdings do not suggest an overall pattern

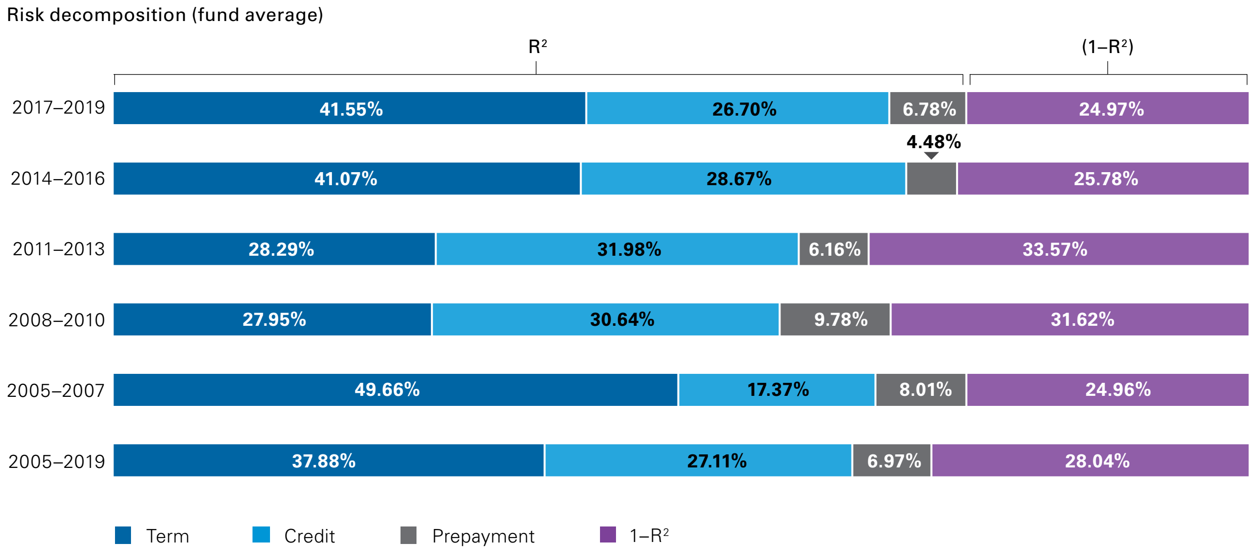


Notes: These scatterplots display the relationship between fund number of holdings and our measures of systematic risk (R^2) and alpha for all fund three-year periods over the 15-year time period ended December 31, 2019. We then group the funds by our three buckets of average credit quality to depict these relationships graphically.
Sources: Morningstar and Bloomberg Barclays.

8 Livingston, Yao, and Zhou (2019) found that greater concentration increases the dispersion of returns and alpha in equity mutual funds.

9 As our measure of systematic risk is made up of the three factors—Term, Credit, and Prepayment—we find no clear relationship between the number of holdings and the regression betas (see Appendix C).

Risk decomposition of systematic risk



Notes: We conducted a Shapley Value regression where we decomposed the systematic risk by each of the fund's underlying factor exposures. The data were calculated for each three-year period over the 15-year time horizon ended December 31, 2019.

Sources: Morningstar and Bloomberg Barclays.

We used the Shapley Value regression technique, which interprets the relative contribution of the independent variables, to decompose each fund's R^2 or systematic risk by the underlying factors: Term, Credit, and Prepayment. This technique was used to confirm that our underlying factors represented most of the systematic risk. The exhibit illustrates the fund average values of systematic and idiosyncratic risk across our five three-year periods and the average values over the 15-year period ended December 2019. While systematic risk dominates over the time periods, we see that the underlying factor compositions vary.

Deciles portfolios of exposures

Having inspected the hypothesized relationship between dependent and independent variables graphically, we next split the sample into deciles that were created based on our explanatory variable (the number of fund holdings) and we analyze fund characteristics based on averages per decile (**Figure 3**).

At first glance, there is no clear linear trend between the number of holdings and R^2 and the number of holdings and alpha across the deciles. However, we do see statistically significant differences between the highest (1st) and lowest (10th) deciles, for R^2 and alpha, respectively, as well as for annualized return, Credit, and Prepayment. The results are consistent with Sapp and Yan (2008), in particular, when comparing the performance of funds based on security concentration in equities.

Regression of systematic risk and alpha on number of holdings

Having gained initial insight about a possible link between fund holdings and a fund's systematic risk as well as its alpha, we test a possible relationship more formally via a regression setup.

Figure 4 represents the results of the second step of our regression and the economic significance of systematic risk and alpha as the dependent variables.[10] The figure illustrates the R^2 and the alpha sensitivity to a change in holdings for the full sample as well as the credit and duration subgroups. From the regression results we are trying to ascertain whether there is a statistical relationship between the number of holdings and 1) systematic risk and 2) alpha.

Figure 3. Alpha and R^2 for highest-decile holdings are statistically different from lowest decile of holdings

			Monthly average alpha and factor exposures				
Holdings decile	Median holdings	Average annualized return (%)	Alpha (%)	Term (%)	Credit (%)	Prepayment (%)	Adjusted R^2
High	*1,455*	*4.12*	*0.05*	*0.24*	*0.19*	*0.31*	*0.73*
2	*737*	*4.20*	*0.04*	*0.23*	*0.28*	*0.25*	*0.74*
3	*519*	*4.46*	*0.06*	*0.21*	*0.35*	*0.21*	*0.75*
4	*408*	*4.34*	*0.03*	*0.21*	*0.36*	*0.18*	*0.76*
5	*324*	*4.38*	*0.04*	*0.23*	*0.38*	*0.14*	*0.75*
6	*258*	*4.88*	*0.04*	*0.24*	*0.46*	*0.07*	*0.77*
7	*205*	*4.44*	*0.03*	*0.23*	*0.33*	*0.10*	*0.73*
8	*151*	*4.15*	*0.05*	*0.22*	*0.28*	*0.12*	*0.68*
9	*102*	*3.99*	*0.04*	*0.22*	*0.23*	*0.12*	*0.69*
Low	*42*	*3.51*	*0.02*	*0.24*	*0.10*	*0.04*	*0.62*
Full sample	*285*	*4.24*	*0.04*	*0.22*	*0.29*	*0.15*	*0.72*
High minus low decile	—	0.58***	0.03**	0.00	0.09***	**0.26*****	**0.10*****
High minus full sample	—	–0.12	0.01	0.02**	–0.10***	**0.16*****	**0.00**
Low minus full sample	—	–0.73***	–0.02**	0.02	–0.19***	**–0.11*****	**–0.10*****

*Statistically significant to 10%; **statistically significant to 5%; ***statistically significant to 1%.

Notes: Statistical difference measured by using 2 sample t-test. Top decile and bottom decile composed of funds with greatest and least holdings, respectively. We form decile portfolios based on fund number of holdings for each three-year period over the 15-year time horizon ended December 31, 2019. We then calculate average fund characteristics based on averages within each decile and across the full sample.

Sources: Morningstar and Bloomberg Barclays.

10 See Appendix D, Panels A, B, and C, for the regression results and economic significance using Term, Credit, and Prepayment, respectively, as the dependent variables.

Figure 4. Regression results show statistical link between systematic risk and number of holdings; however, it is not economically meaningful

Statistical significance:

POS Statistically significant **positive** relationship

NEG Statistically significant **negative** relationship

— No statistically significant relationship

			Sensitivity to R^2 (beta coefficient)		Sensitivity to alpha (beta coefficient)
Full sample (N = 1,940)		POS	0.03***	—	0.00
Credit quality	AAA/AA (N = 377)	—	0.01	—	0.01
	A/BBB (N = 888)	POS	0.10***	—	0.01
	BB/B (N = 675)	—	–0.00	—	0.00
Duration	Ultrashort (N = 83)	—	–0.04	—	–0.00
	Short (N = 527)	—	0.01	—	0.00
	Intermediate (N = 1,244)	—	–0.01	—	0.00
	Long (N = 86)	NEG	–0.07***	—	0.02

*Statistically significant to 10%; **statistically significant to 5%; ***statistically significant to 1%.

Notes: All regressions are controlled for time effects, fund size, and asset manager controls. Base regression model is the most recent time period. Values in boxes represent the Ln holdings coefficients from the regression.

Sources: Morningstar and Bloomberg Barclays.

Measured across the entire sample, we find that R^2 or systematic risk has a beta sensitivity of 0.03, which is statistically significant to 1%. This confirms our first hypothesis: After controlling for size, asset manager, and time effects, we find a positive link between the number of holdings and systematic risk. Alpha, on the other hand, has a beta sensitivity of near zero and is not statistically significant to 1%. This observation runs counter to our second hypothesis because there is no relationship between alpha and the number of holdings for the full sample.

It is reasonable for active fixed income investors to ask whether the number of holdings (all things being equal) can be practically used to manage systematic risk. If we look at the full sample, a 10% change in the number of holdings results in a 0.003 change in R^2 (0.03 * 10% = 0.003 change). Our R^2 sample, based on this change, would increase from 0.724 to 0.727 (0.724 + 0.003 = 0.727), a result that appears to be economically insignificant.

To test the sensitivity of our results, we rerun the regression based on subsamples with funds grouped by credit quality. For the subgroups we see some statistically significant relationships. For R^2, we see statistical significance to 1% for the A/BBB subgroup with a beta sensitivity of 0.10 and –0.07 for the long-duration subgroup. As with the results across the full sample, alpha sensitivity across credit and duration subgroups are near zero and statistically insignificant. While we find some statistically significant relationships in our subgroups, none are economically significant.[11] Based on the results from both the full and subsamples,[12] we find the economic benefit of using the number of holdings to achieve greater systematic risk exposure is de minimis.[13]

11 The highest beta sensitivity is the A/BBB subgroup at 0.10. A 10% change in the number of holdings results in a 0.01 change in R^2 (0.10 * 10% = 0.01 change). In this case, the R^2 for the A/BBB sample would increase only from 0.68 to 0.69 (0.68 + 0.01 = 0.69).

12 Appendix E displays the regression results for each of the 11 Morningstar categories.

13 Additional information on Term, Credit, and Prepayment statistical and economic significance can be found in Appendix B.

Implication of results

A major difference that arises when comparing the number of equity holdings with the number of fixed income holdings is the way in which issuer exposure is interpreted. There is almost always a one-to-one relationship between the equity security held and the issuer exposure in the portfolio. For example, if an equity fund held IBM stock, that would constitute the issuer exposure to IBM (share class notwithstanding).

By contrast, a fixed income security held in a portfolio does not necessarily have a one-to-one relationship with the issuer exposure.[14] At best, if we know the name of the issuer (U.S. Treasury, IBM, Fannie Mae) we can infer whether it is a government, credit, or securitized bond. But far more information is needed to assess a fund's issuer exposure. For example, a fund may hold one fixed income security of an issuer's outstanding bonds, but is it a short-, intermediate-, or long-term bond? Moreover, what type of fixed income security is it? Is it a straight bond, a callable bond? Is it a sinking, floating, or other type of bond?

While we attempted to adjust fund holdings using credit-quality or duration bucket controls, we believe the complexity of issuer exposure across various risk dimensions imposes limits on the use of number of holdings as a pure economic attribute for systematic exposure or alpha potential. Future research could examine the level of systematic risk or alpha potential using a holdings-based approach at the individual bond level.

Conclusion

We examined the relationship between the number of holdings in actively managed fixed income funds and 1) systematic risk as measured by the fund's R^2 as well as 2) fund alpha. While we found a statistically significant positive relationship between the number of holdings and systematic risk, it cannot be regarded as economically significant. Further, we found no statistical link between the number of holdings and fund alpha. Our findings are noteworthy especially when compared with findings made about equity funds.

14 We find a wide range of issues-to-issuer ratios across fixed income benchmarks, from a low of 2.1 for the Bloomberg Barclays U.S. Corporate High Yield Index (1,897 issues and 884 issuers) to a high of 49.7 for the Bloomberg Barclays U.S. Government Index (547 issues and 11 issuers) as of December 31, 2019. In contrast, the issues-to-issuer ratio for the Standard & Poor's 500 Index (505 issues and 500 issuers) is 1.0.

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Appendix A. Factor definitions used for regression analysis

Factor	Definition
Risk-free rate (Rf)	Ibbotson Associates 1-month Treasury bill total return
Term	Bloomberg Barclays Long Term U.S. Treasury Index total return minus risk-free rate
Credit	Bloomberg Barclays U.S. High Yield Index total return in excess of duration-matched U.S. Treasuries
Prepayment	Bloomberg Barclays U.S. Mortgage-Backed Securities Index total return in excess of duration-matched U.S. Treasuries

Appendix B. Morningstar category fund descriptive statistics

					Factor loadings			
	Number of funds	Average number of holdings	Excess return	R^2	Alpha	β_{term}	β_{credit}	β_{prepay}
Full sample	**1,940**	**534**	**4.20**	**0.72**	**0.04**	**0.23*****	**0.30*****	**0.16**
(t-stat)					**(0.32)**	**(8.41)**	**(6.17)**	**(0.57)**
Corporate Bond	79	348	4.96	0.76	0.01	0.35***	0.41***	0.15
					(–0.21)	(9.69)	(6.96)	(0.42)
High-Yield Bond	351	299	6.05	0.91	0.03	0.21***	0.89***	0.02
					(0.15)	(6.06)	(17.27)	(–0.02)
Multisector Bond	110	493	5.24	0.77	0.03	0.26***	0.56***	0.33
					(0.05)	(6.44)	(8.87)	(0.90)
Short Government	114	278	2.46	0.51	0.04	0.11***	0.01	0.02
					(0.38)	(5.43)	(0.38)	(0.13)
Intermediate Government	193	1,278	3.44	0.76	0.05	0.25***	0.01	0.41
					(0.41)	(10.52)	(0.09)	(1.66)
Long Government	17	91	5.96	0.97	–0.02	0.98***	0.01	–0.04
					(–0.51)	(52.49)	(0.44)	(–0.22)
Intermediate Core Bond	287	634	4.01	0.78	0.04	0.28***	0.14***	0.23
					(0.28)	(11.25)	(3.39)	(0.96)
Intermediate Core-Plus Bond	372	670	4.49	0.77	0.06	0.29***	0.23***	0.26
					(0.33)	(10.43)	(5.17)	(0.93)
Ultrashort Bond	82	235	1.93	0.34	0.02	0.02***	0.05***	0.05
					(1.04)	(2.20)	(2.81)	(0.16)
Short-Term Bond	311	366	2.78	0.53	0.05	0.09***	0.10***	–0.02
					(0.57)	(4.86)	(3.35)	(–0.03)
Long-Term Bond	24	221	6.56	0.87	–0.01	0.68***	0.43***	0.29
					(–0.29)	(15.66)	(6.10)	(0.72)

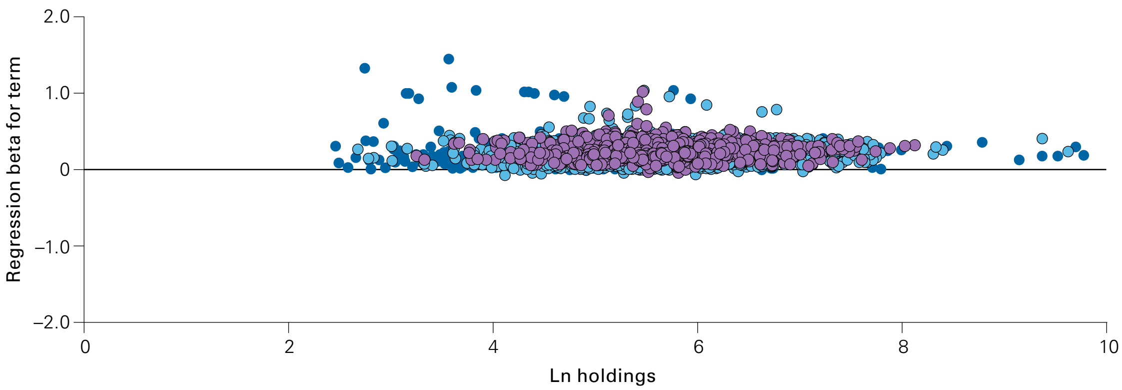
*Statistically significant to 10%; **statistically significant to 5%; ***statistically significant to 1%.

Note: T-statistics are shown in parentheses. A negative value in parentheses means it is a negative t-stat while a positive value in parentheses means it is a positive t-stat.

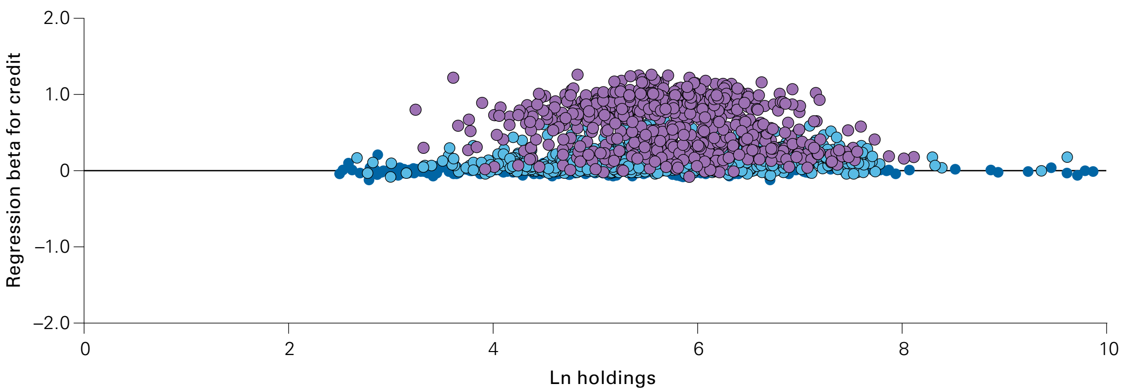
Sources: Morningstar and Bloomberg Barclays.

Appendix C. Factor sensitivities plotted with Ln holdings

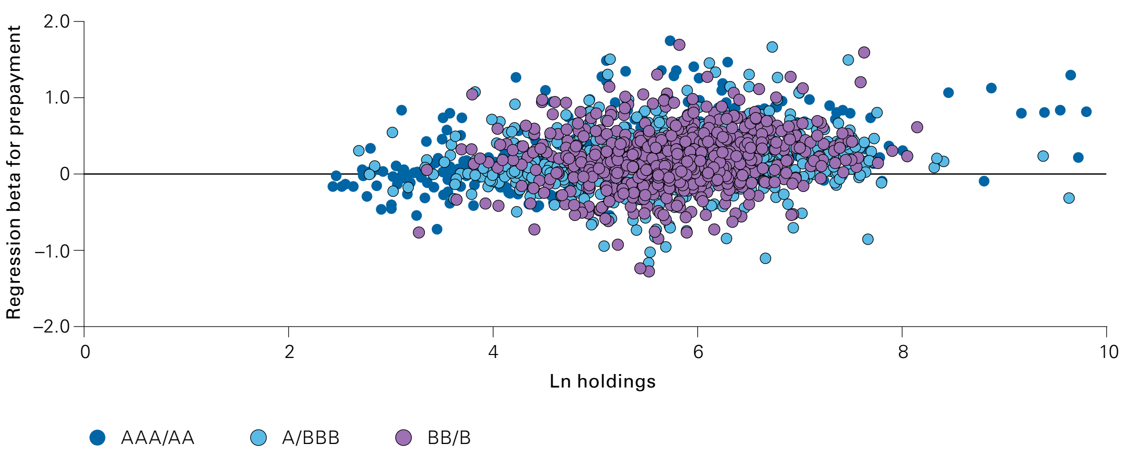
Term versus holdings



Credit versus holdings



Prepayment versus holdings



Sources: Morningstar and Bloomberg Barclays.

Appendix D. Factor sensitivities regressed on number of holdings

Statistical significance:

POS Statistically significant **positive** relationship NEG Statistically significant **negative** relationship — No statistically significant relationship

		Sensitivity to Term (beta coefficient)		Sensitivity to Credit (beta coefficient)		Sensitivity to Prepayment (beta coefficient)	
Full sample (N = 1,940)		—	0.00	—	0.01	POS	0.09***
Credit quality	AAA/AA (N = 377)	NEG	−0.03***	—	0.00	POS	0.17***
	A/BBB (N = 888)	POS	0.04***	POS	0.02***	POS	0.07***
	BB/B (N = 675)	POS	0.03***	NEG	−0.18***	POS	0.06***
Duration	Ultrashort (N = 83)	—	0.00	NEG	−0.05***	—	0.07
	Short (N = 527)	—	−0.01	POS	0.05*	POS	0.04**
	Intermediate (N = 1,244)	POS	0.01***	NEG	−0.05***	POS	0.08***
	Long (N = 86)	NEG	−0.15***	POS	0.20***	—	0.22

*Statistically significant to 10%; **statistically significant to 5%; ***statistically significant to 1%.

Notes: All regressions are controlled for time effects, fund size, and asset manager controls. Base regression model is the most recent time period. Values in boxes represent the Ln holdings coefficients from the regression.

Sources: Morningstar and Bloomberg Barclays.

Appendix E. Number of holdings regressed on R^2 and alpha by Morningstar category

Table legend:

POS Statistically significant **positive** relationship — NEG Statistically significant **negative** relationship — — No statistically significant relationship

Category	Number of funds	R^2-Squared coefficient		Alpha coefficient	
Core plus	372	POS	0.03	—	0.01
High-yield bond	351	POS	0.05	—	−0.01
Short-term bond	311	POS	0.02	POS	0.01
Core bond	287	—	−0.002	—	0.002
Intermediate government	193	NEG	−0.012	—	0.002
Short government	114	NEG	−0.03	—	0.01
Multisector	110	POS	0.04	—	−0.01
Ultrashort bond	82	—	0.03	—	−0.003
Corporate bond	79	POS	0.09	—	−0.01
Long-term bond	24	POS	0.03	—	0.02
Long government	17	—	0.01	—	−0.003

*Statistically significant to 10%; **statistically significant to 5%; ***statistically significant to 1%.

Notes: All regressions are controlled for time effects, fund size, and asset manager controls. Base regression model is the most recent time period. Values in boxes represent the Ln holdings coefficients from the regression.

Sources: Morningstar and Bloomberg Barclays.

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