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An Empirical Analysis of Segmented Pricing of Bond Systematic Risk

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Abstract

This research investigates the existence of segmentation in the market for fixedincome securities. Evidence is found of higher yield spreads being required for non-distressed bonds making larger contributions to the risk of pure debt portfolios over the 2003–2011 period. Abnormal returns existed over that time interval for diversified investors taking long (short) positions on such bonds with higher (lower) betas measured against an index of strictly fixed-income securities.

Eine empirische Analyse von Preissegmentierung bei systemischen Wertpapierrisiken

Zusammenfassung

Mit dieser Forschungsarbeit wird die Existenz von Marktsegmentierung bei festverzinslichen Wertpapieren untersucht. Es gibt Beweise für die Existenz der erforderlichen breiteren Renditemargen für nichtausfallbedrohte Wertpapiere, die größere Beiträge zu dem Risiko reiner Schuldenportfolios während des Zeitraums von 2003 bis 2011 geleistet haben. Während dieses Zeitraums haben breit diversifizierte Anleger, welche Long-(Short) Positionen bei derartigen Wertpapieren mit höherem (niedrigerem) Betafaktor – gemessen am Index für streng festverzinsliche Wertpapiere – gehalten haben, anormale Renditen.

Keywords: bonds, betas, yield spreads, market segmentation, systematic risk

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I. Introduction

In previous studies such as by *Gebhardta*, *Hvidkjaer*, and *Swamina-than* (2005), *Cornell* and *Green* (1991), *Blume*, *Keim*, and *Patel* (1991), and *Weinstein* (1981), bond yields have been found to be positively related to co-movement with bond indexes, stock indexes, and mixed stock-bond portfolios, respectively.¹ However, the linkages between such varied measures of systematic risk and the yield premiums required for them have not been previously investigated.

While there might be a unified pricing of assets in perfectly integrated markets, it is also possible for investment restrictions and frictions to result in segmented valuation of risk across different asset classes. In particular, bond prices may be segmented from stock market values because the current investment environment constrains the portfolios of major fixed-income investors from diversification into equities. For instance, banks and other institutions involved in lending or guaranteeing debts are largely restricted to investing in credit market instruments because of their charters, and other investors such as bond mutual funds are similarly constrained.

The large amount of fixed-income assets held in portfolios restricted only to those investments can lead to bonds being valued less highly when they contribute more to the risk of portfolios consisting only of credit instruments. With many of the largest investors in fixed-income assets not being fully diversified into equities, investors may therefore require special compensation on credit instruments for bonds' co-movement with purely fixed-income portfolios.

Fixed-income investors often evaluate the risk of bonds with parameters like copulas that only measure co-movements between the prices of debt investments (*Tarashev/Zhu*, 2008). Credit betas have also been in use since the 1990s that compute the co-movement between changes in a

¹ In separate studies by *Elton* et al. (2001), and *Lin/Wang/Wu* (2011) that didn't measure systematic risk related to a diversified stock-bond portfolio, bond yields have also been found to be related, respectively, to return covariance with *Fama/French* (1995) factors and to systematic liquidity risk. Because these factors may be integrated with a single beta estimate that measures co-movement with a more complete portfolio of stocks and bonds, the separate components of this lone measure of systematic risk are not separately examined in this study, although they are utilized as regression instruments in one of the empirical tests of this research, and although the premium for pure bond market risk are examined after explicitly factoring out the effects of such variables.

bond's spread and changes in the average spread on a bond index, and that are essentially the same as pure bond betas which compute the covariances between bond total returns (Benzschawel, 2012). In addition, institutional investors in debt assets like bond mutual funds typically have their performance measured relative to other bond portfolios, including via investment alphas estimated by factoring out returns required for systematic risk relative to a 100% bond index (Dietze/ Entrop/Wilkens, 2009). Many traders at investment banks constrained to debt investments are compensated based on Sharpe ratios that calculate the ratio of the average returns on their fixed-income portfolios relative to the return volatility of these strictly credit market positions (Coates, 2012). The latter parameters for investors concentrated in debt investments are optimized by maximizing investment alphas measured using a bond index as the market proxy to adjust for risk. All such segmented measurement of risk in the fixed-income market might affect the yield premiums required on debt assets.

In particular, given that market prices are determined by the average valuation of investors with cross-sectionally varying portfolios that are also subject to differential taxation (*Murphy*, 1990a), bond yield spreads may incorporate compensation strictly for their covariance with an index of fixed-income securities. Systematic risk premiums in the yield spreads on corporate bonds have indeed been empirically found to be significantly related to their volatility (*Benzschawel/Assing*, 2012), as is consistent with a hypothesis of segmented pricing of risk. If this market valuation of purely credit portfolio risk is over and above that required for overall co-movements with a broader market index, investors unconstrained from diversification into equities may be able to increase returns without raising their overall risk by exploiting the segmented pricing of fixed-income securities.

In efficient markets, prices equal the intrinsic values given full information because any market deviations from those values are arbitraged away, and abnormal returns aren't possible (*Fama*, 1970). However, market imperfections like costs associated with valuation analysis and trading have been shown to lead to deviations between price and value (*Grossman/Stiglitz*, 1980). In addition, the generally far larger portion of equity returns in the form of capital gains subject to preferential tax rates for portfolios subject to income taxation might also contribute to persistent segmentation in pricing between the bond and stock markets that can potentially lead to strategies yielding abnormally high pre-tax

profits. The higher tax option value on assets with higher volatility such as equities could also lead to deviations from integrated values that would exist in frictionless markets (*Murphy*, 2001). Moreover, the finite wealth of arbitragers (*Stein*, 1995) and constraints on arbitrager leverage (*Liu/Longstaff*, 2004), as well as motivational, institutional, and marketing limitations on the dissemination of knowledge about lucrative investment opportunities (*Shleifer/Vishny*, 1997), can result in the persistence of abnormally profitable opportunities for those not subject to the market frictions that inhibit integration.

Using option pricing theory to value the securities of individual firms (*Merton*, 1974), evidence of a lack of contemporaneous integrated pricing of equity and debt instruments that might enable profitable arbitrage has been found empirically by *Kapadia* and *Pu* (2012). The latter authors suggested subsequent research to evaluate whether profits could be generated after adjusting for systematic risk.

To investigate the existence of abnormal profits available from any segmented pricing of fixed-income instruments, this study regresses individual bond yield spreads above measures of expected default losses on betas computed against both a strictly fixed-income index and a market portfolio proxy consisting of a stock-bond mix over the 2003– 2011 interval. This regression to determine if return covariance with portfolios consisting of strictly credit instruments is priced indicates that yields on non-distressed bonds are positively related to their contribution to the risk of such typical portfolios of fixed-income investors. The extra yield for such co-movement with pure bond indexes exists even after factoring out the premiums required for various measures of overall market risk.

Evidence is discovered of an implementable arbitrage strategy of buying (selling) non-distressed bonds with higher (lower) betas measured against the returns on a portfolio of pure credit instruments. In particular, positive abnormal returns are found for a strategy of long (short) such bonds with betas measured against a 100 % fixed-income index that are clearly higher (lower) than the median. However, the abnormal returns from buying (selling) these bonds with greater (less) contribution to the risk of a well-diversified portfolio are not significantly positive over all sub-intervals. These results are consistent with the hypothesis of separate pricing of risk in the bond markets, although significant arbitrage profits derived from such segmented pricings are found to be available only over longer holding periods.

In Sections I. and II., respectively, the investigative procedures and data are described. In Section III., the findings are explained, and the results are summarized in Section IV.

II. The Statistical Estimation Procedures

Overall market risk in this study is primarily measured using the betas of *Sharpe's* (1964) Capital Asset Pricing model (CAPM), which indicates a higher return should be required on assets with greater contributions to the risk of a fully diversified portfolio.² However, because regressing raw excess returns on market excess returns to estimate these betas results in a large downward bias in measuring the true systematic risk of still-existing bonds due to actual defaults not being observed over any past sample time horizon for such assets, *Murphy, Lu*, and *Benzschawel* (2013) have suggested modifying the dependent variable in those regressions.³ In particular, the adjusted CAPM beta regression takes the form:

(1)
$$R_j = \alpha_j + \beta_j (r_m - r_f) + v,$$

² While *Fama* and *French* (2004) have cited evidence of deviations of returns being a function of a single beta model in the stock market such as the existence of other priced factors, *Kim* (1997) has empirically discovered that the extra betas found by *Fama/French* (1995) to be related to average returns are much less significant when the statistical problem of error in variables is addressed. In addition, *Jostova/Philopov* (2005) have found risk-return relationships to be adequately characterized by the CAPM when Bayesian estimation procedures are utilized. *Levy/Roll* (2012) have confirmed that the existing empirical evidence is consistent with the CAPM.

³ Bond betas and returns for a given change in required yield spreads have been shown to be linearly related to duration by Jarrow (1978) and Elton et al. (2001), respectively. Because the sample securities used for the tests have to be ones that are still in existence and therefore could not have exhibited actual systematic risk related to defaults, an adjustment to standard procedures for estimating bond betas is necessary to avoid the distortions caused by prior market price changes being a linear function of duration whereas systematic risk related to previously unobserved but possible actual defaults on the still existing bonds is not. In particular, as demonstrated by Murphy/Fu/Benzschawel (2013), each individual bond's raw excess return above the risk-free rate should, before use as the dependent variable in a regression on market excess returns, be multiplied by one plus the ratio of a scalar to the bond's duration, where the scalar has been estimated to equal 4. Use of these duration-adjusted returns normalizes for the large survivorship bias in bond beta estimates to create a portfolio with a duration equal to this multiplier, thereby effectively computing the return that would exist on a portfolio investment in each spot bond and forward contracts on the same debt.

where r is the raw return on the subscripted asset, f and m denote the risk-free one-month Treasury bill and the market portfolio, respectively, R_i is the vector of duration-adjusted monthly total returns on the subscripted bond j in excess of risk-free rates over the prior 60 months that is computed as $[1 + \{4/\text{duration}\}][r_i - r_i]$, the α and β parameters to be estimated are the investment alpha and market beta of the subscripted asset, and v is the residual.

For this study of bond risk-return tradeoffs, it seems to be important to specify a proxy for the entire market portfolio used in (1) that includes fixed-income instruments as well as stocks. As a result, an asset mix consisting of 60% in the S&P 500 (that is a weighted average return for 500 large stocks), 30 % in the Citigroup Broad Investment Grade (BIG) index (that is a capitalization-weighted average of the over 4000 large investment grade issues of treasury, agency, corporate, and asset-backed securities excluding commercial mortgage-backed debts and inflation-indexed bonds), and 10% in the Citigroup High Yield Cash Pay (HYCP) index (that is a capitalization-weighted average of large corporate cashpaying issues rated below investment grade) is used for m. This market proxy is comparable to that used by in the seminal work by *Gatti* (1983) to estimate market portfolio betas for bonds, except that a junk bond index replaces a weighting for pure Treasury bonds because BIG incorporates Treasury debt and because the junk bond market has since become a significant portion of the market portfolio.

Generalized Least Squares (GLS) beta estimates, which correct for heteroscedasticity and autocorrelation as explained in Greene (2012), are used to supply initial estimates of the betas in (1). They are further adjusted using Bayesian procedures, which require a simple adjustment of individual beta estimates toward a population mean (Vasicek, 1973), that provide more accurate measures of the contribution of an asset to the risk of a diversified portfolio (Frost/Savarino, 1986). The Bayesian estimation method, which is utilized in this research because it is consistent with both standard practices and actual market pricing in empirical tests on the equity markets, involves multiplying the initial estimates for each bond by 2/3 and then adding the product of 1/3 and the average beta estimate for all assets in that investment class (Murphy, 1990b).

A similar regression framework is employed for estimating each individual bond's contribution to the risk of a pure bond portfolio

(2)
$$r_j - r_f = \alpha_j' + \beta_j' (r_m' - r_f) + v',$$

where an apostrophe after a variable denotes parameter values using a pure bond portfolio as the market proxy consisting of the same relative weighting utilized in the broader index, i.e., 75 % into BIG and 25 % into HYCP. Each bond's raw excess returns $r_j - r_f$ are utilized as the dependent variable in (2) because the systematic risk relative to pure bond portfolios that is relevant to many investors is generally measured without an adjustment for distortions related to unobserved systematic default risk on still existing bonds (*Murphy*, 2010). Multiplying by a factor to adjust for such biases would therefore be inappropriate when determining if there is market segmentation relating to those risk measures. In addition, because Bayesian beta estimators are largely confined to investors with positions in the equity markets (*Statman*, 1981), an unadjusted Generalized Least Squares (GLS) estimator is utilized for this beta.

In order to evaluate the existence of premiums for different types of bond risk, the following regression framework is employed

(3)
$$S - L = p_0 + p_1 \beta + p_2 \beta' + e,$$

where S is the spread between the bond's yield to maturity and the yield to maturity on a Treasury bond with the same duration, L is the annual expected value of the default losses on the debt based on historical relationships between the bond's credit rating and past defaults, the betas are estimated over the prior 60 months using (1) and (2), each p parameter with a different subscript is a price of risk to be estimated, and e is the regression error. As in *Elton, Gruber, Agrawal*, and *Mann's* (2001) introductory investigation into the determinants of yield spreads, subtracting expected default losses from bond spreads before regressing them on measures of systematic risk, as in (3), enables separating out that component of risk. The variable for this cost of bankruptcy risk L is measured using the *Murphy* (1988) procedure of employing past default losses on bonds of each credit rating that has been updated by *Murphy* (2000).⁴

⁴ These estimates are used for L instead of those from *Elton* et al. (2001) because the latter have unrealistic estimates like a 0% chance of default for most investment grade debt near term. In addition, the latter researchers' modeling of default risk for a bond of a given credit rating as a function of maturity disregards the fact that the maturity of the bonds is taken into consideration by the credit rating agencies, which already incorporate these effects on default risk that are associated with the possibility of future changes in companies' credit standing (*Ganguin/Bilardello*, 2005). In contrast, the *Murphy* (2000) estimates that assume that credit ratings do incorporate the impact of bond maturity and thus reflect

The intercept in (3) enables factoring out any systematically higher premium required for expected default losses that are in excess of those which have occurred in the past, thereby preventing such a bias in estimating L from be attributable to the beta regressors. Any general premium required for liquidity risks, such as caused by the relative illiquidity of all corporate bonds relative to Treasury issues, which act as money substitutes with respect to being universally accepted as repo collateral that is especially important during financial crises (*Krishnamurthy*/*Vissing-Jorgensen*, 2012), may also be picked up by this p_0 parameter.

Because the independent variables in (3) are measured with error, an instrumental variables (IV) estimator is employed for this regression (Greene, 2012). The instruments that affect the systematic risk in a diversified portfolio are specified to be the three OLS Fama and French (1995) factor betas, beta estimates set as a linear function of the credit rating of each bond (Murphy, 1988), the GLS beta measured against the S&P500, Elton et al.'s (2001) estimates for default losses that incorporate effects relating to credit rating changes over time, the 1-month T-bill rate, and several measures of liquidity that include one divided by the amount of the bond issue outstanding in millions of dollars, the number of years since issue, and the number of years to maturity.⁵ To adjust for heteroscedaticity found to exist in *Breusch* and *Pagan* (1979) tests, regression (3) is weighted by the product of the absolute value of the *t*-statistics for β from (1) and β ' from (2) that are raised to respective powers equal to $-\frac{1}{2}$ the regression coefficient of the logged squared OLS residuals from (3) on the logged squares of these t-statistics (Greene, 2012).

The robustness of any findings of extra yields being required for pure bond market risk is evaluated using alternative asset pricing models. Since *Liu*, *Shi*, *Wang*, and *Wu* (2009) have found bond yield spreads are

the average default rate over the life of the bond are more consistent with the employment of agency ratings.

⁵ Prior studies such as by *Murphy* (1998), *Krishnamurth* (2002), and *Lin/Liu/Wu* (2011), respectfully, have found these latter three instruments for liquidity to be priced. See footnote #1 for an explanation and references for use of these instruments that may also be components of CAPM betas and thus justify their employment in the IV estimator employed in this study to adjust for the bias caused by error in measuring the true return on the market portfolio of all assets. Other liquidity measures, such as those which de *Jong/Driessen* (2012) found to be associated with over 0.6% of the risk premium available on investment grade bonds without factoring out the pricing of risk relative to pure bond portfolios nor to an integrated market portfolio of both equity and credit instruments, could also be employed in future integrated research.

significantly related to the three *Fama* and *French* (FF) betas which measure risk relating to market-to-book and size factors as well as an index of stock market returns, systematic risk estimated relative to these variables are substituted for β in regression (3) in order to determine whether extra spreads are required for β' even after factoring out premiums for those risk measures. In addition, because *King* and *Khang* (2005) have found yield spreads to be highly related to factors such as credit rating and duration as well as a tax factor proxy in the form of the coupon rate, regression (3) is also conducted using these variables to determine if yields are related to β' even after controlling for those variables that might be highly related to the pure bond betas⁶.

The opportunity for arbitrage profits using only ex-ante data to construct an investment strategy is also investigated. In particular, ex-post returns can be measured each month on a portfolio constructed using an equal-weighted long position in the bonds with the highest ex-ante β' and an equal-weighted short position in the ones with the lowest estimated contribution to the risk of pure fixed-income portfolios. Because including the short positions on bonds might lead to offsetting negative alphas for taking only a long position on bonds in general, abnormal profits may be possible with this strategy despite the possibility of an overall overpricing of fixed-income investments caused by some investors being restricted to the debt markets bidding up their prices. Although special costs and constraints on short sales might make such abnormal profits difficult to realize in practice, use of the very liquid market for credit default swaps (CDSs) might enable circumventing these expenses and restrictions.

To determine if this investment strategy generates significant abnormal profits, the returns on this long-short portfolio g are regressed on the excess returns on the 60-30-10 index above the risk-free rate

(4)
$$r_g = \alpha_g + \beta_g (r_m - r_f) + z_g,$$

⁶ Fama/French (1993) found bond returns to also be related to the excess returns on Treasury bonds as well as the difference between Treasury and corporate bond returns. However, the authors found that those variables explained only a tiny amount of average bond returns. In addition, it is conceivable that those factors merely reflected a time lag in reported price changes between the Treasury and corporate bond markets due to stale prices and illiquidity, which might have been acute for many bonds in their sample that covered a much earlier time interval. As a result, there appears little justification for including these or other variables in the regression.

The raw returns on g are used as the dependent variable in (4) because the long holdings in the portfolio are funded by the short positions. In particular, since the cash thereby freed up could technically be invested into risk-free T-bills, the excess returns on *g* for investors so investing the cash would equal r_q . The intercept in (4) represents the ex-post investment alpha, or abnormal risk-adjusted return, on this position that can be tested for significance from zero.

bonds being misclassified as contributing more (less) to the risk of pure credit portfolios than the median sample bond when they actually contribute less (more). Since such misclassifications can bias statistical results toward insignificance, a 3-group method is utilized (Kmenta, 1986) that eliminates all bonds with β ' in the middle half of the sample. This strategy involves long positions on the bonds with pure bond betas in the highest quartile and short positions on the bonds with β' in the lowest quartile. Besides measuring the standard investment alpha from the strategy relative to overall market risk using regression (4), abnormal returns are also measured when replacing the independent variable in (4) with the 3 FF factors, which Fama and French (1993) have found to be related to the market returns of at least low-grade bonds.

The investment alpha for the long-short portfolio may be of especially great interest to investors diversified into both equities and bonds. While any financial institutions serving public shareholders might optimally be concerned only with sufficient compensation for the systematic risk of diversified portfolios in perfect markets, the costs of financial distress that might be associated with pure bond market variation may motivate many such fixed-income investors to value lower co-movements with their portfolios of fixed-income instruments. In particular, bankruptcy risk can reduce the value of the growth option for stocks as well as negatively impact both the amount of tax-deductible debt capital companies can obtain and the cost of that financial leverage, thereby negatively affecting the value of their equity (Murphy, 2000). As a result, return covariation with purely fixed-income portfolios may very well be priced because it increases the risks and costs of financial distress for institutional investors restricted to positions in credit instruments. Arbitraging away any resulting mispricings might be difficult if the level of abnormal returns available to diversified investors from trading in segmented markets is too low to justify the market frictions of trading like transaction costs.

Because β' is measured with error, there is the possibility of some

III. Data

The index and individual bond data for the tests consisting of monthly observations on all the bonds in BIG or HYCP over the interval 1998–2011 that have no embedded options like call or conversion features, that have maturities under 100 years, and that have S&P credit ratings are provided by Citibank. Using the 60 months prior to the observation month for each bond to estimate its beta for that period, this sample consists of 335,113 in-sample observations over the interval 2003–2011.

Other data are procured from Computstat, including monthly total S&P 500 stock returns and the yields on one-month T-bills, which are utilized as the risk-free rate in all cases. The Fama-French factors are obtained from those authors' website http://mba.tuck.dartmouth. edu/pages/faculty/ken.french/data_library.html.

The mean, median, and range of the relevant variables in the utilized data set are shown in Table 1. Each of the sample bonds has at least \$100 million outstanding. As a result, since a premium yield for illiquidity has been found to be less than 2 basis points for bonds of that size (*Murphy*, 1998), and since such large corporate bond issues have average transaction costs of only about 10 basis points (*de Jong* and *Driessen*, 2012), there is justification for not including a particular proxy for a premium yield required for expected trading expenses in (3). Any premiums required for the particular systematic liquidity risks of individual issues are incorporated into the measure of β , which should efficiently pick up such effects because of the employment of several instruments for liquidity risk in (3).

The correlation between the variables across all months and bonds used in the test are shown in Table 2. The high correlation of 0.63 between β and β' indicates the strong association between these variables that can result in both diversified investors and those institutions restricted to credit instruments requiring similar yield premiums for their highly related contribution to the risks of those different portfolios. Both raw yield spreads (S) and those adjusted for expected default losses (S – L) are more than twice as correlated with β as with β' , thus indicating the relatively greater significance of overall market risk in determining bond prices.

(1)	(2)	(3)	(4)	(5)	(6)
			Standard		
Variable ^a	Mean	Median	Deviation	Max.	Min.
Panel A. Full sample (r	n = 335, 113)				
S	2.75	1.57	4.12	99.06	-15.23
L	0.50	0.22	0.65	2.61	0.04
S - L	2.25	1.22	3.83	98.52	-17.84
3	0.51	0.40	0.77	24.93	-13.96
3'	1.15	1.00	1.02	25.91	-34.71
3St&p500	0.10	0.02	0.37	12.11	-7.91
Rating	0.25	0.24	0.11	0.54	0.03
3 _{FF1}	0.16	0.07	0.49	23.87	-13.88
$3_{\rm FF2}$	-0.02	-0.04	0.65	42.83	-52.15
S _{FF3}	0.01	0.02	0.64	33.43	-20.96
Elton	0.87	0.25	2.03	17.45	0.00
f	0.15	0.09	0.15	0.44	0.00
Coupon	6.53	6.50	1.48	16.75	0.00
Par Value (\$Millions)	577.91	400.00	541.80	7364.00	100.00
Time on the run	4.72	4.00	3.45	29.00	0.00
Fime to Maturity	9.86	6.00	10.32	95.00	1.00
Duration	5.88	4.99	3.96	92.93	0.48
Panel B. Investment G	rade (n = 26	36,058)			
5	1.86	1.26	2.24	98.65	-8.44
_	0.21	0.17	0.12	0.44	0.04
S - L	1.65	1.04	2.22	98.52	-8.88
3	0.37	0.34	0.40	7.62	-5.69
3'	1.05	0.96	0.63	9.44	-12.23
S&P500	0.03	-0.02	0.22	3.52	-3.91
Rating	0.21	0.21	0.06	0.30	0.03
FF1t	0.08	0.03	0.32	23.87	-12.98
3 _{FF2}	-0.07	-0.05	0.50	42.83	-52.15
FF3	0.01	0.02	0.49	33.43	-20.96
Elton	0.21	0.18	0.17	0.72	0.00
f	0.15	0.10	0.15	0.44	0.00
Coupon	6.21	6.20	1.29	15.00	0.00
Par Value (\$Millions)	617.67	425.00	560.02	6500.00	200.00
Time on the run	4.53	4.00	3.38	24.00	0.00
Fime to Maturity	10.12	7.00	10.49	95.00	1.00
Duration	6.09	5.27	4.15	92.93	0.48

Table 1

Bond Characteristics (Monthly Observations, 2003–2011)

(1)	(2)	(3)	(4)	(5)	(6)
			Standard		
Variable ^a	Mean	Median	Deviation	Max.	Min.
Panel C. Junk (n = 69,0	55)				
S	6.21	4.60	6.93	99.06	-15.23
L	1.63	1.72	0.62	2.61	0.86
S - L	4.57	3.02	6.74	96.45	-17.84
В	1.04	0.77	1.38	24.93	-13.96
β'	1.52	1.19	1.83	25.91	-34.71
$\beta_{\mathrm{S\&P500}}$	0.38	0.26	0.62	12.11	-7.91
$\beta_{ m Rating}$	0.41	0.39	0.07	0.54	0.33
$\beta_{ m FF1}$	0.47	0.33	0.82	19.71	-13.88
$\beta_{ m FF2}$	0.18	0.12	1.03	36.94	-19.39
$\beta_{ m FF3}$	0.01	0.07	1.04	17.40	-20.23
$L_{ m Elton}$	3.39	1.52	3.44	17.45	0.74
r_f	0.14	0.08	0.15	0.44	0.00
Coupon	7.77	7.60	1.51	16.75	0.00
Par Value (\$Millions)	424.69	300.00	432.00	7364.00	100.00
Time on the run	5.48	5.00	3.63	29.00	0.00
Time to Maturity	8.84	6.00	9.55	95.00	1.00
Duration	5.05	4.34	2.95	30.73	0.48

^a S is the promised yield spread above T-bonds with the same duration, β is the regression (18) Bayesian GLS beta relative to a 60-30-10 portfolio of the S&P 500, the BIG index, and the HYCP index, respectively that utilizes the subscripted duration-adjustment parameter H, L is the expected default losses given past defaults on bonds based on just the existing credit ratings.

_				(e)	(a)		(Q)	(e)	(0+)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(01)
	S	L	S - L	β	β,	$\beta_{\mathrm{S\&P50.0}}$	$B_{ m Rating}$	$B_{ m FF1}$	$B_{ m FF2}$	$B_{ m FF3}$	$L_{ m Elton}$	r_f	Coupon	Coupon Par Value	T/run	T/run Maturity Duration	Duratic
	1.00																
	0.51	1.00															
- L	0.99	0.38	1.00														
	0.41	0.44	0.37	1.00													
	0.20	0.27	0.17	0.64	1.00												
	0.40	0.47	0.36	0.93	0.54	1.00											
	0.48	0.90	0.36	0.41	0.26	0.44	1.00										
eta_{FFmkt}	0.34	0.38	0.30	0.75	0.51	0.78	0.36	1.00									
		0.16	0.05	0.04	0.07	0.03	0.15	-0.15	1.00								
	-0.06	0.00	-0.07	-0.05	0.01	-0.05	0.00	-0.29	-0.16	1.00							
	0.51	0.80	0.42	0.48	0.34	0.46	0.71	0.39	0.14	-0.01	1.00						
	-0.22 -	-0.08	-0.22	-0.16	0.07	-0.21	-0.09	-0.16	-0.05	0.14	-0.09	1.00					
Coupon	0.24	0.46	0.18	0.17	0.18	0.22	0.49	0.18	0.13	0.03	0.37	-0.11	1.00				
Par Value –	-0.05	-0.15	-0.03	0.02	0.00	0.02	-0.21	0.02	-0.04	-0.03	-0.10	-0.03	-0.09	1.00			
	0.06	0.10	0.05	0.03	0.01	0.06	0.08	0.03	0.04	0.01	0.06	0.00	0.35	-0.17	1.00		
Maturity -	-0.02	-0.05	-0.02	0.05	0.28	0.07	-0.02	0.06	-0.01	0.02	-0.04	0.01	0.13	-0.04	0.13	1.00	
Duration -	-0.09	-0.11	-0.07	0.03	0.30	0.04	-0.07	0.05	-0.03	0.01	-0.07	0.01	0.08	-0.03	0.06	0.85	1.00

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IV. The Results

An introductory test is conducted of the relationship between bond spreads and pure bond betas after controlling for numerous factors which might affect spreads that *Khang* and *King* (2005) have found to be related to *S*. As indicated with the regression results reported in Table 3, a regression of spreads (adjusted for expected default losses) on β ' indicated a positive significant relationship when the bonds' FF betas, coupon rate, duration, proxies for liquidity (amount outstanding and time on the run), and credit rating dummy value (equal to 1 for AAA and increasing by 1 for each sign/letter reduction in the rating) are also included as independent variables.

The results of the GLS IV panel regression (3) are reported in Table 4.⁷ The parameter estimate of about 1 % for p_0 is consistent with a premium yield being required by investors for the relative illiquidity of corporate bonds in general relative to Treasuries. The positive significant intercept may also reflect a market expectation of default losses that are higher than implied by past failure rates by agency rating. The significant parameter estimate for β ' when it is the only variable in the regression indicates a positive relationship between yield spreads and betas measured against a 100 % fixed-income portfolio. Similar results were found when the sample was segmented into investment grade and junk bond issues.

However, the negative significant parameter estimate for p_2 when β is included in the regression implies lower risk-adjusted yields actually being required on bonds with higher pure betas after factoring out the return attributed to co-movement with the 60-40 stock-bond portfolio. This latter finding may stem from multicollinearity between β and β' (as indicated in Table 2) that might result in (3) assigning especially high premiums for bonds with credit risk perceived by the market to be much higher than implied by their current credit ratings and the past default losses on bonds of that quality. In particular, the yields required for default risk on those bonds would be far above *L*, and this extra spread just

⁷ GLS was empirically found to be necessary because *Breusch-Pagan* statistics indicated (not shown) statistically significant heteroskedasticity relative to the cross-sectional beta *t*-statistics. However, the sign and significance of the parameter estimates in Table 4 were unaffected by the use of unweighted least squares. In addition, similar results for that table were found when OLS was employed (i.e., without weighting or IV). The utilization of Bayesian GLS pure bond betas as opposed to the GLS β ' estimates also didn't have a material impact on the findings.

Table 3

Relationship Between Pure Bond Betas and Yields/Returns^a (2003–2011)

 $S - L = f(\beta^{\circ}, B_1, B_2, B_3, Coupon, Duration, CreditRating, Par$ Amount, Time on run)$

	Mod	el 1	Mode	el 2	Mod	el 3
	Coefficient	(t)	Coefficient	(t)	Coefficient	(t)
Intercept	-0.82	-26.74*	-1.06	-36.50*	-0.56	-17.57*
β'	1.78	169.63*	1.28	118.56*	1.79	168.69*
B_1	-0.10	-59.18*	-0.10	-63.91*	-0.10	-59.08*
B_2	0.12	38.81*	0.12	40.20*	0.12	38.83*
B_3	-0.11	-37.47*	-0.10	-39.17*	-0.11	-37.62*
Coupon	0.33	72.57*	0.05	9.90*	0.32	66.92*
Duration	-0.19	-105.70*	-0.13	-76.27*	-0.18	-104.80*
CreditRating			0.28	124.28*		
Par\$ Amount	÷				-0.01	-15.52*
Time on run					-0.03	-13.65*

* Statistically significant from 0 at the <.10 level.

^a The OLS dependent variable S - L is the spread S above Treasury rates after subtracting out the expected value of default losses L is regressed on β_1 , β_2 , and β_3 are the bond betas estimated against the 3 FF factors (consisting of the excess return on the stock market, the return to an SMB portfolio long on stocks with the smallest (largest) market capitalization, and the return on an HML portfolio long stocks with the lowest (highest) market-to-book ratios, respectively), Coupon rate, Duration, CreditRating dummy values (rising by one for each reduction in the sign/letter rating), Par\$ Amount, and Time on the run.

to compensate for market expectations of default losses might be falsely attributed to β because these bonds would represent a greater claim on firms' equity and thus move more with the stock market (which is only included in the 60-30-10 index used to estimate β but is not in the pure bond index employed to estimate β '). The result can be an overestimate of p_1 that biases the estimate of p_2 downward due to β and β ' being positively correlated. The larger correlation of L with β than with β ' reported in Table 2 is consistent with this hypothesis.

The latter distortion is removed by purging all those bonds with S - L in excess of those that might normally be required for systematic risk. Removing bonds with yield spreads that are inconsistent with their credit ratings has previously been suggested by *Elton* et al. (2001) in order to minimize distortions caused by deviations between estimates of default losses estimated by the market and those indicated by credit ratings. Systematic risk premiums are likely constrained to be below 3 % (*Murphy*,

Table 4

Relationship Between Pure Bond Betas and Yields/Returnsa (2003–2011)

	-	0 1 1/ 1	2,			
	p_0	(<i>t</i>)	p_1	(<i>t</i>)	p_2	(<i>t</i>)
Full Sample	1.23	90.22*	2.21	160.41*	-0.17	-12.39*
	0.49	36.92*			1.57	156.78*
Investment	1.33	137.01*	2.11	163.92*	-0.45	-51.35*
	1.33	121.03*			0.30	30.72*
Junk	3.77	80.47*	1.59	32.92*	-0.45	-8.22*
	3.18	77.40*			1.11	47.04*
Full Sample	6.21	138.95*	2.34	44.75*	-1.25	-22.34*
	5.31	133.78*			1.00	47.15*
Investment	5.09	110.98*	2.77	46.85*	-1.17	-21.02*
	4.73	91.83*			0.86	19.35*
Junk	7.30	97.81*	2.07	29.34*	-1.26	-16.20*
	6.24	93.43*			0.84	29.66*
Full Sample	0.87	239.04*	0.42	101.14*	0.08	21.40*
	0.80	223.20*			0.29	96.72*
Investment	0.76	221.40*	0.56	119.17*	0.13	38.56*
	0.77	219.39*			0.30	98.67*
Junk	1.22	98.23*	-0.11	-7.38*	0.22	14.45*
	1.27	113.23*			0.12	15.73*
Full Sample	0.88	242.09*	0.74	102.85*	0.04	10.88*
	0.79	222.27*			0.30	99.74*
Investment	0.78	227.89*	0.91	119.41*	0.09	27.12*
	0.76	216.62*			0.31	101.68*
Junk	1.24	101.63*	-0.15	-5.28*	0.19	11.90*
	1.28	115.16*			0.11	15.01*
	Investment Junk Full Sample Investment Junk Full Sample Investment Junk Full Sample Investment Investment Investment	Full Sample 1.23 0.49 1nvestment 1.33 Junk 3.77 Junk 3.77 Junk 3.77 Junk 5.31 Full Sample 6.21 Junk 7.30 Junk 7.30 Junk 0.87 Junk 0.76 Junk 0.77 Junk 0.77 Junk 1.22 Full Sample 0.87 0.77 0.80 Investment 0.76 0.77 0.30 Investment 0.76 0.77 0.79 Junk 0.79 Investment 0.78 0.79 0.78 0.79 0.76 Junk 0.76 Junk 0.78 0.76 0.76 Junk 0.76 Junk 1.24	Full Sample 1.23 90.22* 1.049 36.92* Investment 1.33 137.01* 1.33 121.03* Junk 3.77 80.47* Junk 3.77 80.47* Junk 3.77 80.47* Junk 3.77 80.47* Junk 3.78 77.40* Full Sample 6.21 138.95* Junk 5.09 110.98* 4.73 91.83* 91.83* Junk 7.30 97.81* 6.24 93.43* 93.43* Full Sample 0.87 223.20* Investment 0.76 221.40* 0.77 219.39* 113.23* Junk 1.22 98.23* 1.27 113.23* Full Sample 0.88 242.09* 0.79 222.27* Investment 0.78 227.89* 0.76 216.62* Junk 1.24 101.63*	Full Sample 1.23 90.22* 2.21 0.49 36.92* Investment 1.33 137.01* 2.11 1.33 121.03* Junk 3.77 80.47* 1.59 Junk 3.77 80.47* 1.59 Junk 3.77 80.47* 1.59 Junk 3.78 77.40* Full Sample 6.21 138.95* 2.34 Junk 7.30 91.83* Junk 7.30 97.81* 2.07 6.24 93.43* Full Sample 0.87 239.04* 0.42 0.80 223.20* Investment 0.76 221.40* 0.56 0.77 219.39* Junk 1.22 98.23* -0.11 1.27 113.23* Full Sample 0.88 242	Full Sample 1.23 90.22* 2.21 160.41* 0.49 36.92* 160.41* 1.33 137.01* 2.11 163.92* Investment 1.33 137.01* 2.11 163.92* Junk 3.77 80.47* 1.59 32.92* Full Sample 6.21 138.95* 2.34 44.75* Sila 77.40* 46.85* 4.73 91.83* Junk 7.30 97.81* 2.07 29.34* 6.24 93.43* - - 11.14* 0.80 223.20* 101.14* 0.80 223.20* 111.14* Investment 0.76 221.40* 0.56 119.17* Junk 1.22 98.23* -0.11 -7.38* 1.27 113.23* - - - Full Sample 0.88	Full Sample1.2390.22*2.21160.41* -0.17 0.49 36.92^* 1.57Investment1.33 137.01^* 2.11 163.92^* -0.45 1.33 121.03^* 0.30Junk 3.77 80.47^* 1.59 32.92^* -0.45 3.18 77.40^* 1.11Full Sample 6.21 138.95^* 2.34 44.75^* -1.25 5.31 133.78^* 1.00Investment 5.09 110.98^* 2.77 46.85^* -1.17 4.73 91.83^* 0.86Junk 7.30 97.81^* 2.07 29.34^* -1.26 6.24 93.43^* 0.84Full Sample 0.87 223.20^* 0.29Investment 0.76 221.40^* 0.56 119.17^* 0.13 0.77 219.39^* Junk 1.22 98.23^* -0.11 -7.38^* 0.22 Investment 0.76 224.99^* 0.74 102.85^* 0.04 0.79 222.27^* 0.30 0.30 Investment 0.78 227.89^* 0.91 119.41^* 0.09 0.76 216.62^* 0.31 0.31 Junk 1.24 101.63^* -0.15 -5.28^* 0.19

 $S - L = p_0 + p_1\beta + p_2\beta' + e$

* Statistically significant from 0 at the <.10 level.

^a The pure bond betas β ' are measured with a GLS regression of the monthly return for each bond in excess of the risk-free short-term Treasury rate on the excess return on a pure bond portfolio consisting of $\frac{4}{3}$ BIG and $\frac{1}{4}$ HYCP. In contrast, the total market systematic risk β are estimated from a GLS regression of the excess monthly return for each bond (adjusted for duration distortions) on the excess returns for a market proxy consisting of 60 % invested into the S&P500, 30 % invested into BIG, and 10 % invested into HYCP, with an adjustment for a Bayesian prior. Both betas are estimated using the data over the 60 months prior to the observation month. Spreads *S* denote the cross-sectional time-series of each bond's monthly yield spread above interest rates on T-bonds with the same durations, while *L* represents a variable for default risk based on the credit rating and past default rates. The regression is run with an IV GLS estimator that adjusts for both error in variables and heteroscedasticity measured relative to the *t*-statistics for the bond estimates.

^b Full sample results.

^c Sample with observations purged where dependent variable S - L < 3 %.

^d Sample with observations purged where dependent variable S - L > 3 % purged.

 $^{\rm e}$ Sample with observations purged where dependent variable $S-L>3\,\%$ purged and non-duration adjustment.

2000), and so only observations with S - L < 3% are used for this purged data set.⁸ The results of (3) using this group of bonds are shown in Table 4. As indicated there, the p_2 estimates become positive even when β' is included in the regression. As also shown in Table 4, similar results were obtained when there was no adjustment for survival biases in measures of systematic risk for still existing bonds, i.e., when β was estimated using raw excess returns in (1).⁹ These findings provide empirical evidence in support of the hypothesis that investors do indeed require separate compensation for the contribution of fixed-income securities to the risk of portfolios concentrated in credit instruments.

In contrast, regression (3) run on the other subsample of bonds for which S - L > 3% indicated no positive extra yield required on bonds with higher β . These findings may stem from the particular credit instruments in this subsample representing distressed bonds upon which investors require very high yields for their large expected value of default losses that may result in them being classified as substandard or non-performing assets by regulated financial institutions. Such investors may therefore be motivated by regulatory capital requirements to avoid such investments and liquidate many of them if they are held. Since those large investors constrained into pure credit portfolios would not normally hold the bonds in this subsample, there may not be extra returns required on distressed bonds for their contribution to the risk of portfolios concentrated in fixed-income instruments.

In fact, *Benzschawel, Lee*, and *Li* (2013) have found that investors require a relatively lower risk-adjusted yield on the bonds of companies financed proportionally more with debt because such investments allow fixed-income investors like hedge funds concentrating on fixed-income investments to effectively obtain more leverage. Since margin requirements normally limit borrowings to finance bond investments without regard to overall portfolio risk, greater risk taking by such investors is

⁸ Although not shown, the correlation between β and β' for this purged sample is reduced to 0.50 by doing so, thus implying lower multicollinearity. This reduction is especially important in regression (3) because they are highly related to true market consensus estimates of L that are incorporated into prices and that are far higher than those implied by the credit ratings for some bonds, as explained in the text.

⁹ In addition, though not shown, use of a scalar equal to 1.18 (instead of 4) as the duration adjustment to measure bond excess returns in (1) that has also been suggested by *Murphy/Fu/Benzschawel* (2013) as a means of estimating β did not change the sign and significance of the parameter estimates.

possible by taking positions on bonds with greater contributions to the variation in their pure fixed-income portfolios. For this reason, distressed bonds, which tend to be obligations of companies with more financial leverage, may have lower returns relative to their pure credit betas than others. The significant negative p_2 parameter estimate when regression (3) is run on the subsample of bonds with S - L > 3 % provides confirming evidence for this hypothesis.

To test whether it is possible to profit from the market segmentation using only ex-ante information to construct investment positions from the sample of bonds with S - L > 3%, a portfolio is formed each month that is equally long in the quartile of the sample's bonds with the highest pure credit betas and short in the quartile with the lowest β ' estimated using (2) with only ex-ante data. The returns on this portfolio are then regressed on the excess returns of the 60-30-10 market portfolio proxy as indicated in (4), and the results are displayed in Table 5. The findings indicate this strategy generated a statistically significant positive intercept for the sample of bonds with S - L < 3%.

In order to evaluate the robustness of these results, regression (4) with the sample of bonds with S - L < 3% was run with betas measured relative to the three FF factors substituted for the excess return on the overall market. The results shown in Table 6 indicate these factors explained little of the return on the long-short portfolio except with respect to junk debt, as is consistent with the findings of *Fama* and *French* (1993) in studying pure long portfolios. Most importantly, though, the intercept or alpha for the long-short portfolio based on the size of β ' remained significantly positive for both investment grade and junk bonds after control-ling for the FF factors via the Table 6 regression.¹⁰

 $^{^{10}}$ It is interesting to observe in Table 6 the statistical insignificance of the Fama-French factors in explaining any of the long-short bond portfolio returns except with respect to the junk sub-sample over the first half interval. Within this context, it may be instructive to note that the alpha estimated using the FF factors to measure risk was significantly positive (not shown) when OLS was employed for purposes of constructing the long-short portfolio g, just as it was when the 3-group method was used as shown in Table 5. The finding of significance even without separation of the bonds with β ' estimates closest to the median (that are most likely to be placed into the wrong end of the long-end portfolio due to estimation error) may stem from the three factors in FF model not picking up the full systematic risk of bonds as there are no bonds at all in any of the three FF asset groupings whose returns determine the FF factors (thus resulting in the misclassifications about the relative size of pure bond return co-movement being a less important consideration when only factoring out those FF measures of risk). In

Table 5

Abnormal Returns to an Investment Grade Portfolio Long on Bonds with High Betas Relative to a 100% Bond Index and Short on the Others^a (Monthly data, 2003–2011)

· y · y · µy · µy										
	Portfolio	α_g	(t)	β	(t)	R^2				
	Full Sample	0.10	0.98	0.27	8.17*	0.41				
$Non-Purge^{\mathrm{b}}$	Investment Grade	0.15	1.17	0.16	3.75*	0.13				
	Junk	-0.12	-0.69	0.53	9.41*	0.47				
	Full Sample	0.25	1.57	0.16	3.15*	0.09				
Purge	Investment Grade	0.21	1.27	0.15	2.83*	0.08				
$S - L > 3\%^{c}$	Junk	0.57	1.74*	0.27	2.56*	0.06				
	Full Sample	0.12	0.63	0.36	5.71*	0.25				
S - L > 3%	Investment Grade	0.31	1.39	0.26	3.72*	0.13				
$only^{d}$	Junk	0.25	1.05	0.56	7.26*	0.35				
	Full Sample	0.42	1.78*	0.22	2.81*	0.07				
	Full Sample – 1 st Half ^f	0.01	0.05	0.42	3.19*	0.16				
	Full Sample – 2 nd Half ^f	0.75	1.68*	0.19	1.74*	0.06				
Purge	Investment Grade – Full	0.36	1.47	0.21	2.56*	0.06				
S - L > 3%,	Investment Grade – 1 st Half ^f	-0.02	-0.07	0.40	2.67*	0.12				
$75\% - 25\%^{e}$	Investment Grade – 2^{nd} Half ^f	0.66	1.47	0.18	1.63	0.06				
	Junk – Full	1.05	1.63	0.48	2.16*	0.05				
	Junk – 1 st Half ^f	0.18	1.27	0.49	6.09*	0.42				
	$Junk - 2^{nd} Half^{f}$	2.17	1.49	0.52	1.37	0.05				

r_a	=	α_a	+	$\beta_g(r_m$	_	$r_{\rm f}$)	+	v_a
· 9		-g		ry (* m		•)/		- y

* Statistically significant from 0 at the <.10 level.

^e Sample with observations purged where dependent variable S - L > 3% (and long in the sample bonds with the highest 25% pure bond betas β 'and short in the lowest 25%).

^fThe First Half denotes the initial sub-interval 2003–2007 while the Second Half denotes the 2007–2011 period for the Full Sample 2003–2011.

contrast, Table 5 indicates a positive alpha that is statistically insignificant from zero for the 2-group long-short portfolio when the single beta model is employed. These overall results are consistent with OLS results being distorted by error in estimating β' leading to a misclassification of which bonds make higher contributions to the risk of pure credit portfolios for those with β' closer to the median.

^a The monthly returns r_g are measured on a portfolio long in the sample bonds with the highest pure bond betas β' (measured against an index consisting of % BIG and ¼ HYCP) and short in those with the lowest β' , where the betas used to form the portfolios anew each month are computed using the data available over the 60 months prior to each observed monthly return. The OLS regression intercept α_g measures the abnormal return or alpha on the portfolio (that has no net investment) while the β_g estimates the systematic risk of the portfolio relative to a market index consisting of 60 % invested into the S&P500, 30 % invested into BIG, and 10 % invested into HYCP.

^b Full sample results.

^c Sample with observations purged where dependent variable S - L > 3 %.

^d Sample with observations purged where dependent variable S - L < 3 %.

Table 6

Abnormal Returns to an Investment Grade Portfolio Long on Bonds with High Betas Relative to a 100 % Bond Index and Short on the Others (Monthly data, 2003–2011)

	Portfolio	α_p	(<i>t</i>)	β_1	(<i>t</i>)	β_2	(<i>t</i>)	β_3	(t)	R^2
	Full Sample	0.51	2.07*	0.09	1.50	-0.06	-0.52	-0.10	-0.90	0.02
	Full Sample – 1 st half ^c	0.16	0.59	0.14	1.33	-0.14	-1.08	0.08	0.51	0.05
Purge	Full Sample – 2 nd half ^c	0.73	1.54	0.10	1.13	0.04	0.18	-0.16	-0.95	0.04
Furge S–L > 3%,	Investment Grade	0.46	1.79*	0.08	1.27	-0.08	-0.64	-0.08	-0.75	0.02
75%-25% ^b	$Inv - 1^{st} half^{c}$	0.15	0.50	0.12	1.02	-0.16	-1.16	0.08	0.46	0.04
	$Inv - 2^{nd} half^c$	0.65	1.34	0.09	1.01	0.03	0.16	-0.15	-0.89	0.03
	Junk	1.15	1.77*	-0.01	-0.09	0.45	1.54	-0.43	-1.56	0.05
	$Junk - 1^{st} half^{c}$	0.23	1.27	0.24	3.34*	-0.05	-0.54	0.08	0.74	0.21
	$Junk - 2^{nd} half^c$	1.54	1.02	-0.01	-0.04	1.02	1.58	-0.72	-1.41	0.09

 $r_g = \alpha_g + \beta_1(r_s - r_f) + \beta_2 \text{SMB} + \beta_3 \text{HML} + z$

* Statistically significant from 0 at the <.10 level.

^a The monthly returns r_g are measured on a portfolio long in the sample bonds with the highest pure bond betas β' (measured against an index consisting of % BIG and % HYCP) and short in those with the lowest β' , where the betas used to form the portfolios anew each month are computed using the data available over the 60 months prior to each observed monthly return. The OLS regression intercept α_g measures the abnormal return or alpha on the portfolio (that has no net investment) while the β_1 , β_2 , and β_3 estimates the systematic risk of the portfolio relative to the Fama-French factors that consist of the excess return on the stock market, the return to an SMB portfolio long on stocks with the smallest (largest) market capitalization, and the return on an HML portfolio long stocks with the lowest (highest) market-to-book ratios, respectively.

^bSample with observations purged where dependent variable S - L > 3% (and long in the sample bonds with the highest 25% pure bond betas β 'and short in the lowest 25%).

^c The First Half denotes the initial sub-interval 2003–2007 while the Second Half denotes the 2007–2011 period for the Full Sample 2003–2011.

These findings imply that abnormal profits can be earned by diversified investors concentrating on debt with clearly higher contributions to the risk of pure bond portfolios.¹¹ The monthly risk-adjusted excess return of over 0.4 % for the aggregate sample implies an annual abnormal re-

¹¹ Note, however, that the statistical insignificance of the alphas when the sample is partitioned into junk and investment grade portfolios indicates significantly higher returns for β ' exist only for portfolios that include both segments. This finding is consistent with the bond market being integrated across these two sectors. This result implies that banks which invest into both investment grade and junk debt, as opposed to bond mutual funds typically specializing in either the lower or higher quality segments, are most likely the primary cause of the segmentation of the bond and equity markets.

turn in excess of 5 %. Given the low transaction costs in the bond market of 0.1 % (*de Jong/Driessen*, 2012) and only moderate portfolio turnover resulting from the monthly rebalancing (4.42 % not shown), these arbitrage profits would still be close to 5–6 % annually net of trading expenses, which would reduce the monthly alpha by less than 1 basis point. The low overall market beta of 0.22 for this strategy implies very little systematic risk for diversified investors exploiting the apparent segmented pricing of risk in the credit markets.¹²

However, Tables 5 and 6 also show the investment alpha for this strategy of exploiting the evident market segmentation is statistically insignificant from zero over the shorter 2003–2007 interval. Abnormal returns are significantly positive only in the second sub-interval.¹³ These results imply that investors may have to maintain the strategy over long time horizons to obtain significant profits.¹⁴

The overall evidence indicates some special valuation of pure fixedincome risk, as may be caused by many institutional investors being constrained to holding only non-distressed debts.¹⁵ While banks with diver-

¹⁴ Of course, as for any trading strategy, long-term profits are also not guaranteed, as increased awareness and exploitation of an arbitrage opportunity will eventually eliminate the potential abnormal returns available from it (*Peters*, 2003). In particular, increased buying (selling) of bonds with higher (lower) pure bond betas would cause the pricing of risk to be more integrated across the markets.

 15 Kapudia and Pu's (2012) results indicating debt and equity markets aren't fully integrated, are consistent with the existence of this type of market segmentation. In particular, their findings that bond prices sometimes lead stock prices and vice-versus may stem from premiums for systematic risk in the two markets

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¹² Although not shown, separating the long and short portions of the overall long-short portfolio based on β ' quartiles indicated the highest alphas are on the long side of the portfolio. This finding implies that the underpricing is on the bonds with higher β ' and that a strategy of taking long positions on those debts alone might be sufficient to generate abnormal returns for diversified investors.

¹³ The insignificant alphas over the 2003–2007 interval may stem from the fact that sellers of CDS insurance had the incentive to maximize risk then because the lack of disclosure and regulation in that market enabled them to benefit from the upside of risk-taking while not participating fully in the downside due to limited liability and even implied government bailouts (*Murphy*, 2011). Their trading might lead to arbitraging pressure on the prices of bonds with higher β ' that might offset the relatively less demand for those fixed-income instruments by financial institutions seeking to maximize the rest of the credit portfolios. Some greater regulatory oversight, disclosure, and improved clearing procedures for CDSs after the financial crisis might have inhibited some of the motivation to engage in risk maximizing practices, thus resulting in the observed significantly higher risk-adjusted returns on bonds with higher β ' in the second sub-interval as well as for the entire 2003–2011 sample.

sified shareholders might rationally require compensation for the contribution of such bonds to the volatility of their largely higher-grade fixed-income portfolios because of the financial distress costs stemming from such risk, there may be methods of hedging such risk cheaply enough to justify greater allocation of theses portfolios to bonds with higher systematic credit market risk to enable earning the large abnormal returns discovered here.¹⁶

V. Conclusion

This research empirically examines whether higher yield spreads are required by investors for bond return covariance with an index of fixedincome instruments that is separate from the systematic risk relative to a more complete market proxy of stocks and bonds. The empirical investigation uncovers evidence of segmentation between the equity and credit markets that leads to bonds' contributions to the risk of pure fixedincome portfolios being priced differently than it would be by well-diversified investors. Significant investment alphas for well-diversified investors are found to have existed in the past from exploiting this market inefficiency, at least with respect to non-distressed bonds which have clearly differentiated pure bond betas.

The market segmentation between the stock and bond markets may be caused by so many large financial institutions being constrained to portfolios consisting largely of credit assets.¹⁷ The findings of this study indi-

temporally varying in non-synchronous ways that may lead to such lead-lag relationships.

¹⁶ In addition, such institutions might investigate alternative methods to reduce bankruptcy risk. For instance, *Murphy* (1997) has shown that a company buying puts on its own stock can be an effective method of decreasing the chance of financial distress. Issuing reverse convertibles represent one means used by some companies to effectively take long put positions on their own stock.

¹⁷ Future research might test whether premium returns in the stock market exist for pure bond market risk. An initial investigation of such premiums was conducted by regressing the excess returns on the stocks of the companies whose bonds were included in the sample on the factors listed in Table 3. The findings indicated no positive relationship to the pure bond betas and in fact resulted in a significantly negative parameter estimate for that independent variable. In addition, the Table 6 regression run on the 3 FF factors using the stocks of the companies in the long-short portfolio (instead of the bonds) resulted in an intercept that was statistically insignificant from zero. Thus, the abnormal returns available on bonds with higher β ' doesn't seem to exist on equities, but the exact structure of segmented premiums in the stock market merits much further study.

cating arbitrage opportunities for investors diversified into both equities and fixed-income instruments stem from the resulting separate pricing of pure bond market risk. However, the empirical results indicate that investors might be able exploit the inefficient integration across markets only over long time horizons.

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