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The Bond-Pricing Implications of Rating-Based Capital Requirements

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Abstract

This article demonstrates that rating-based capital requirements, through their impact on insurers' investment demand, affect corporate bond prices. Consistent with insurers' low demand for investment-grade bonds with a rating close to noninvestment-grade, these bonds outperform. Consistent with insurers' high (low) demand for investment-grade bonds with high (low) systematic risk exposure, these bonds underperform (outperform). Insurer demand, measured by insurer holdings, explains most of these pricing effects. We identify rating-based capital requirements as the driver of insurer demand, and thus the pricing effects, by showing that the effects do not exist before these requirements' implementation in 1993.

I. Introduction

This article examines whether rating-based capital requirements affect asset prices. An extensive literature shows that capital regulations impact the investment decisions of regulated firms and thus their demand for assets with certain characteristics (e.g., Pennacchi (2006), Becker and Ivashina (2015), and Iannotta, Pennacchi, and Santos (2019)). Recent theoretical work links investor demand for assets with

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certain characteristics to asset prices (e.g., Koijen and Yogo (2019)). In particular, the model of Harris, Opp, and Opp (2019) formalizes the argument that capital regulations, through their impact on regulated firms' investment decisions, cause equilibrium asset prices to diverge from their frictionless benchmark. In this article, we provide empirical support for this argument using U.S. corporate bonds.

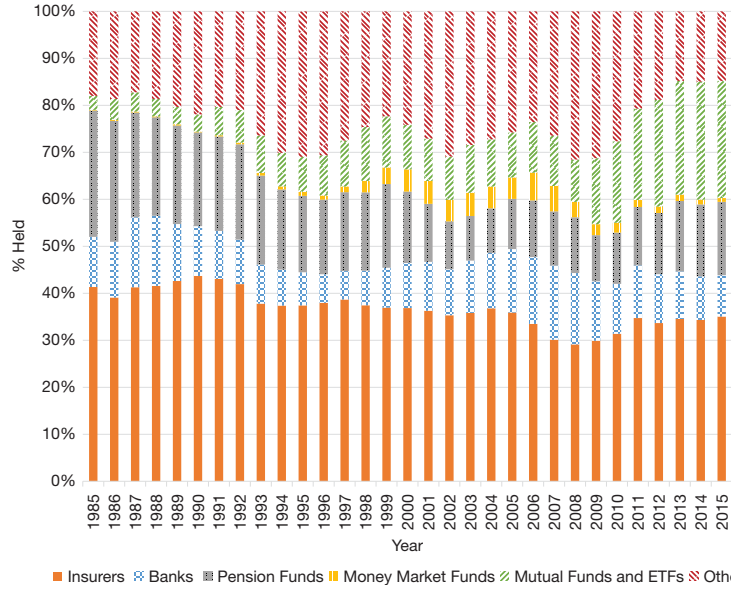
The U.S. corporate bond market offers an ideal setting to investigate how rating-based capital requirements affect asset prices for 2 main reasons. First, insurers are the most important players in this market, owning more than a third of the market value outstanding (see Figure 1) and accounting for a large portion of trading volume (Bessembinder, Maxwell, and Venkataraman (2006)). To the extent that insurers are large investors in corporate bonds, the impact of their investment decisions on prices is likely to be substantial. Second, insurers' rating-based capital requirements create incentives to invest in corporate bonds with certain characteristics. These incentives lead to 2 specific predictions about patterns in bond prices that are attributable to insurers' capital regulations.

The first prediction derives from the literature's empirical finding that high capital charges for noninvestment-grade (NIG) bonds encourage insurers to quickly sell bonds downgraded from investment-grade (IG) to NIG (Ambrose, Cai, and Helwege (2008)), which results in large but short-lived underpricing of these bonds by a median of 7% (Ellul, Jotikasthira, and Lundblad (2011)). We argue that insurers, aware of the potential impact of these fire sales, preemptively avoid investing in IG bonds with a rating close to NIG, resulting in low demand for

FIGURE 1

Investors in the Corporate Bond Market

Figure 1 presents the proportion of U.S. and foreign corporate bonds held by major U.S. investor types. Insurers are both life insurers and property/casualty insurers. Data come from the Federal Reserve Statistical Release Z.1, Financial Accounts of the United States for the periods 1985–1994, 1995–2004, and 2005–2015.



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such bonds. Thus, our first prediction is that, as a result of low demand, the prices of bonds with high NIG proximity (IG bonds with a rating close to NIG) are lower than those predicted by frictionless equilibrium models (frictionless benchmark hereafter).

Our second prediction is based on the theoretical argument that because rating-based capital requirements do not fully reflect systematic risk, when coupled with guaranty funds, they create an incentive for insurers to increase systematic risk taking (Pennacchi (2006)). Therefore, among bonds in the same capital charge category, insurers can boost expected portfolio return by tilting holdings toward (away from) high-systematic (low-systematic) risk exposure bonds (Becker and Ivashina (2015)), thereby creating high (low) demand for such bonds and impacting equilibrium prices (Frazzini and Pedersen (2014)). Thus, our second prediction is that, as a result of high (low) demand, conditional on required capital charge, the prices of bonds with high (low) systematic risk exposure are higher (lower) than the frictionless benchmark.

We test our two bond-pricing predictions by examining a comprehensive sample of IG corporate bond returns from the period of 1993–2014, when rating-based capital requirements for insurers are in place.[1] Specifically, we analyze the risk-adjusted returns of bond portfolios designed to have variation in NIG proximity or systematic risk exposure. Bonds with prices that are above (below) the frictionless benchmark should generate negative (positive) future risk-adjusted returns. In support of our first prediction, we find that high-NIG proximity bonds, which we define as bonds with the lowest IG rating (BBB−), generate positive risk-adjusted returns, whereas the performance of better-rated bonds is commensurate with their risk exposure. In support of our second prediction, we find that, conditional on capital charge, bonds with high (low) systematic risk exposure generate negative (positive) risk-adjusted returns. These pricing effects last for at least 12 months after portfolio formation, indicating that they reflect persistent equilibrium pricing and distinguishing our findings from those of studies that document temporary price pressure in the corporate bond market (Ellul et al. (2011), Ellul, Jotikasthira, Lundblad, and Wang (2015), and Dick-Nielsen and Rossi (2019)).

We next test whether the detected pricing patterns are a manifestation of insurer investment demand. First, we examine whether insurers do indeed tilt their portfolios away from bonds with a rating close to NIG and toward (away from) bonds with high (low) systematic risk exposure. As predicted, regression and portfolio analyses demonstrate that insurers underweight bonds rated BBB− and overweight (underweight) bonds with high (low) exposure to systematic risk.

[1]We focus on the IG segment of the corporate bond market for 2 reasons. First, insurers are collectively the most important institutional investors in IG bonds, but they hold only a small proportion of NIG bonds (Becker and Ivashina (2015); Nikolova, Wang, and Wu (2020)). Insurers' limited presence in the NIG segment of the corporate bond market makes it less likely that their investment preferences affect NIG bond prices. Second, NIG corporate bonds account for a small portion of insurers' investments. Using data from insurers' regulatory filings for the 2002–2014 period, we find that only 9% of insurers' corporate bond holdings are rated NIG (i.e., have an NAIC designation in the 3–6 range as described in Table IA-1 of the Supplementary Material). Thus, within the NIG corporate bond segment, insurers may be less likely to act on investment incentives created by rating-based capital requirements, because doing so will have a minimal impact on their overall investment income.

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We then investigate the extent to which insurer investment demand explains the observed pricing patterns. Our tests indicate that the patterns associated with NIG proximity and systematic risk exposure are strongly related to insurer holdings. Taken together, these results suggest that the outperformance of bonds with high NIG proximity and the underperformance (outperformance) of bonds with high (low) systematic risk exposure are driven by insurer investment demand.

Finally, we examine whether rating-based capital requirements drive the observed patterns in insurer investment demand and, therefore, are ultimately responsible for the documented pricing patterns. Rating-based capital requirements for insurers were implemented in 1993. Because this regulatory change was debated for several years prior to implementation and penalties for undercapitalized insurers under the new requirements were phased in over several years, we do not expect to observe a structural break in 1993. However, we do expect that the patterns in insurer holdings and bond pricing are, on average, different in the period before 1993 than those in the period after. Consistent with our expectation, the same tests that provide strong evidence of pricing patterns during the 1993–2014 period fail to detect any such patterns during 1978–1992. Examining both periods together, our results indicate that the risk-adjusted performance of the portfolios we analyze is significantly different during the period in which rating-based capital requirements are in place. Further analyses reveal that explanations based on intermediary asset pricing, insurer asset–liability matching, and factor model misspecification are inconsistent with our findings.

Our work contributes to three broad strands of research. First, we add to a growing literature on the unintended consequences of regulatory reliance on credit ratings. Pennacchi (2006) and Iannotta et al. (2019) develop theoretical models to demonstrate that rating-based capital requirements create incentives for regulated firms to increase systematic risk exposure. Acharya and Richardson (2009), Calomiris and Mason (2010), White (2010), Cornaggia, Cornaggia, and Hund (2017), and Stanton and Wallace (2018) provide empirical evidence that rating-based capital requirements lead to various forms of regulatory arbitrage by financial firms. Most closely related to our work, Ellul et al. (2011), Becker and Ivashina (2015), and Nanda, Wu, and Zhou (2019) show that insurers' investment decisions induced by rating-based capital requirements have important implications for the U.S. corporate bond market. Ellul et al. (2011) demonstrate that fire sales by insurers around downgrades from IG to NIG cause short-lived deviations of market prices from fundamental values. In contrast, we find that insurers' persistent aversion to IG bonds with high NIG proximity (i.e., bonds that have not been downgraded to NIG but are at the IG–NIG threshold) causes these bonds' equilibrium prices to diverge from their frictionless benchmark. Becker and Ivashina (2015) show that, conditional on capital charge, insurers' IG primary market purchases tilt toward high-risk bonds. We provide the price effects counterpart to the quantity effects they document by showing that insurers' demand for bonds with high-systematic risk exposure impacts equilibrium prices. Finally, Nanda et al. (2019) argue that investors other than insurers command a premium for the risk associated with insurer fire sales, which increases in insurer ownership. Although they find that yield spreads increase in insurer holdings *within* bonds of the same rating and the same risk, we present evidence that insurer holdings vary strongly *across* ratings and risk, and this cross-characteristic

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variation in insurer holdings is negatively related to cross-characteristic variation in average risk-adjusted bond returns. Another important distinction between these 3 latter studies and ours is that we demonstrate that insurers' demand affects the prices of a large cross section and long time series of IG corporate bonds; we examine more than 20,000 unique bonds over the entire 1993–2014 period when rating-based capital requirements for insurers are in effect.

Second, our article adds to the literature on the asset-pricing implications of institutional investor demand (e.g., Koijen and Yogo (2019)). Harris et al. (2019) develop a theoretical model in which bank capital requirements that measure the risk of assets imperfectly cause distortions in the cross section of asset prices. Frazzini and Pedersen (2014) document a negative relation between risk-factor exposure and risk-adjusted returns in several asset classes, and suggest that it is driven by mutual fund and pension fund demand resulting from leverage constraints. Other work has documented persistent distortions in the pricing of stocks (Gompers and Metrick (2001)) and loans (Ivashina and Sun (2011)) due to institutional demand. Our article finds deviations from frictionless benchmark prices in the corporate bond market and attributes them to insurer demand induced by rating-based capital requirements. To the best of our knowledge, we are the first to empirically link demand-based pricing distortions to capital regulations.

Finally, our article contributes to the empirical asset-pricing literature by providing new evidence on the cross section of corporate bond returns. Jostova, Nikolova, Philipov, and Stahel (2013), Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017), Choi and Kim (2018), Crawford, Perotti, Price III, and Skousen (2019), and Cao, Goyal, Xiao, and Zhan (2020) show that anomalies previously documented in the equity market are present in the corporate bond market as well. Our article adds to this literature by demonstrating that rating-based capital requirements, which are unique to credit markets, have important implications for the cross section of expected bond returns.

II. Hypotheses

In this section, we discuss how incentives created by risk-based capital (RBC) requirements influence insurers' investment decisions and, in turn, affect equilibrium bond prices. Based on this discussion, we develop 5 testable hypotheses that are the basis of our empirical investigation.

RBC requirements for insurers were introduced in 1993 to counter the risk-taking incentives created by state guaranty funds (Section IA-I of the Supplementary Material provides a detailed discussion of the regulatory background).[2] Specifically, regulators adopted the ratio of actual capital (i.e., total adjusted capital) to required capital (i.e., authorized control level RBC), referred to as the RBC ratio, as the primary measure of insurer capital adequacy. Although required capital considers a number of risk sources, the risk of the insurer's investment portfolio is one of the most important. Since insurers invest primarily in fixed-income securities, and of these corporate bonds are the most represented asset class, the

[2]The NAIC's Risk-Based Capital Model Act became effective in 1993. For more details, see http://www.naic.org/documents/prod_serv_statistical_rsn_lb.pdf.

credit quality of an insurer's corporate bond holdings has a first-order impact on its RBC ratio.[3]

For capital adequacy assessment purposes, the credit quality of corporate bonds is assessed by the National Association of Insurance Commissioners' (NAIC) Securities Valuation Office, which assigns each security in an insurer's portfolio an NAIC designation.[4] Designations take integer values from 1 to 6 with higher numbers implying worse credit quality and requiring more capital.[5] For corporate bonds, NAIC designations are exclusively based on credit ratings issued by approved credit rating providers (CRPs), with the best-rated NIG bonds requiring significantly more capital than the worst-rated IG bonds.[6] Furthermore, because required capital charges are based on credit ratings, bond risk not captured by ratings is irrelevant for regulatory capital purposes.

We argue that the incentives created by these 2 features of insurers' rating-based capital requirements influence insurers' investment decisions, and ultimately bond prices, in 2 specific ways. First, empirical studies demonstrate that rating-based capital requirements play an important role in insurers' decision to dispose of securities downgraded from IG to NIG. Ambrose et al. (2008) show that insurers engage in greater selling of bonds downgraded from IG to NIG than of comparable bonds that are not downgraded, and Ellul et al. (2011) provide evidence that such insurer "fire sales" temporarily depress prices by a median of 7%. The findings of these studies suggest that waiting to sell a bond with a worsening credit quality until after it is downgraded to NIG can be costly. The costs associated with holding such bonds create a strong incentive for insurers to proactively avoid investing in IG bonds with high NIG proximity. Therefore, we expect that the low insurer demand for such bonds results in a lower equilibrium price than predicted by frictionless benchmark models.

Second, investment portfolio returns are a primary source of income for insurers and essential for their ability to cover claims. Since guaranty funds allow insurers to take on risk without bearing its full cost, insurers have an incentive to increase expected returns by taking more systematic risk. The model in Pennacchi (2006) formalizes this argument in the context of bank deposit insurance and investment incentives. The model's main takeaway is that when deposit insurance is priced to be actuarially fair (i.e., the expected payout is discounted at the risk-free rate) but not economically fair (i.e., the expected payout is discounted at a risk-adjusted rate), banks can increase their market value by increasing systematic risk taking. The same exact reasoning, applied to the insurance industry, suggests that guaranty funds give insurers an incentive to take on more systematic risk than they would in the absence of such funds.

[3]Corporate bonds account for an average of 37% of insurers' investments during 1993–2014 based on data from the Federal Reserve Statistical Release Z.1, Financial Accounts of the United States.

[4]Although insurers are regulated at the state level, capital regulations are coordinated through the NAIC and all states use the same NAIC designations and required capital charges (Becker and Ivashina (2015)).

[5]Table IA-1 in the Supplementary Material summarizes the mapping from ratings to NAIC designations and, in turn, to required capital charges.

[6]The current list of approved CRPs includes 9 companies (Moody's, S&P, Fitch, DBRS, A.M. Best, Morningstar, Kroll, Egan Jones, and HR Ratings de Mexico), but during the majority of our sample period, insurer regulators relied on Moody's, S&P, Fitch, DBRS, and A.M. Best. In our analysis, we focus on credit ratings by Moody's, S&P, and Fitch.

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Without the constraint imposed by capital requirements, insurers can increase systematic risk either by tilting their portfolios toward high-systematic risk exposure securities or by levering up their investments in low-systematic risk exposure securities. Prior to 1993, insurers had no reason to favor one approach over the other, since early capital regulations did not meaningfully limit either. This changed with the adoption of rating-based capital requirements, which restricted insurers' ability to increase leverage but not their ability to select riskier securities. Since within each NAIC designation there are bonds with different systematic risk exposures, conditional on NAIC designation, insurers can overweight (underweight) bonds with higher (lower) systematic risk without increasing required capital.[7] Frazzini and Pedersen (2014) model the equilibrium effects of leverage constraints on investor holdings and security prices. In their model, leverage-constrained investors optimally overweight (underweight) securities with high-systematic (low-systematic) risk and the equilibrium prices of such securities are higher (lower) than they would be absent the constraints. Hence, conditional on NAIC designation, we expect that high (low) demand by insurers for bonds with high (low) systematic risk results in higher (lower) equilibrium prices than predicted by frictionless benchmark models.

For the demand induced by insurers' rating-based capital requirements to have the predicted effects on bond prices, two assumptions must hold. First, insurers must be sufficiently large investors in IG corporate bonds to have a substantial effect on the demand curves of the bonds they underweight or overweight. This assumption is strongly supported by Figure 1, which shows that insurers are the largest investors in corporate bonds, holding about a third of the total market value outstanding. Second, the supply curves for the bonds insurers underweight or overweight must not be perfectly elastic. While this assumption is likely to hold in the short run, in the long run, firms may opt to issue more (fewer) of the types of bonds whose prices have been pushed above (below) the frictionless benchmark by insurer demand, thereby changing the total supply of such bonds. However, Colla, Ippolito, and Li (2013) find that firms are reluctant to switch from one type of debt to another, and empirical evidence from the equity and loan markets (Shleifer (1986), Gompers and Metrick (2001), and Ivashina and Sun (2011)) indicates that firms do not sufficiently adjust their financing decisions to eliminate price effects coming from demand by important market participants. These results suggest that, even in the long run, the supply curves for bonds may not be perfectly elastic.

Our reasoning above leads to 5 testable hypotheses that are the focus of the remainder of the article. Hypotheses 1 and 2 (H1 and H2) relate to the pricing patterns we expect to observe as a result of insurers' low demand for IG bonds that have high NIG proximity and high (low) demand for IG bonds that have high (low) systematic risk exposure.

Hypothesis 1 (H1). IG bonds with high NIG proximity generate positive average risk-adjusted returns.

[7]Becker and Ivashina (2015) and Iannotta et al. (2019) provide empirical evidence that insurers and commercial banks, respectively, act on these incentives.

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Hypothesis 2 (H2). Conditional on capital charge, IG bonds with high (low) systematic risk exposure generate negative (positive) average risk-adjusted returns.

Our next hypotheses, H3 and H4, identify insurer demand as the driver of the pricing effects described in H1 and H2.

Hypothesis 3 (H3). Insurers' portfolio holdings are tilted away from bonds with high NIG proximity and toward bonds with high systematic risk exposure.

Hypothesis 4 (H4). There is a negative relation between insurers' portfolio holdings and average risk-adjusted bond returns.

Since H1–H4 are all a manifestation of incentives created by insurers' rating-based capital requirements, we test these hypotheses using data from the period when these requirements are in place.

Our final hypothesis, H5, ties insurer demand to rating-based capital requirements through bond performance. It is plausible that NIG proximity and systematic risk exposure may drive both insurers' portfolio holdings and risk-adjusted bond returns, yet the latter may not be the direct result of the former. To establish rating-based capital requirements as the driver of insurer holdings and thus bond performance, we compare the period before to the period after the requirements' implementation. Since insurer holdings data during and prior to the 1990s are unavailable, we are unable to investigate whether these holdings are different in the 2 periods. Our hypothesis is, therefore, related to bond performance.

Hypothesis 5 (H5). During the period prior to the implementation of rating-based capital requirements, the pricing patterns described in H1 and H2 do not exist.

Although we cannot completely rule out that another market or regulatory change at the time rating-based capital requirements were implemented may have impacted bond prices, empirical support for H5 would corroborate our assertion that capital regulations are the ultimate driver of the pricing patterns we hypothesize.

III. Data and Sample

Before proceeding to tests of our hypotheses, we describe our data and sample construction.

A. Bond Returns and Characteristics

Following Jostova et al. (2013) and Chordia et al. (2017), bond returns are constructed using data from 4 different sources that cover different time periods: i) Lehman Brothers' Fixed Income Database (Lehman, 1973–1998), ii) Thomson Reuter's Datastream (Datastream, 1990–2014), iii) Mergent's NAIC Database (MNAIC, 1994–2014), and iv) FINRA's TRACE (TRACE, 2002–2014). Section IA-II of the Supplementary Material describes each data source in detail. We define the return of bond i in month t, $r_{i,t}$, as:

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$$r_{i,t} = \frac{(P_{i,t} + \mathrm{AI}_{i,t} + C_{i,t}) - (P_{i,t-1} + \mathrm{AI}_{i,t-1})}{P_{i,t-1} + \mathrm{AI}_{i,t-1}}, \tag{1}$$

where $P_{i,t}$ is the bond's clean price at the end of month t, $\mathrm{AI}_{i,t}$ is the bond's accrued interest at the end of month t, and $C_{i,t}$ is the bond's coupon paid during month t. When we combine returns from the 4 different data sources, we give precedence to trade-based returns by using the sources in the following sequence: TRACE, MNAIC, Lehman, and Datastream.[8] To ensure data quality, we follow Jostova et al. (2013) and remove the bottom and top 0.5% of return observations. Finally, we define the excess return of bond i in month t, $R_{i,t}$, as the return of the bond minus the return of the 1-month U.S. Treasury bill.[9]

Bond ratings and other characteristics come from several sources and are measured for each bond i at the end of each month t. Data on S&P, Moody's, and Fitch ratings come from Thomson Reuters' DataScope. To determine a bond's rating for regulatory capital purposes when ratings from multiple CRPs are available in the same month, we follow the insurers' regulatory capital guidance and use the lower rating when 2 are available and the second lowest rating when 3 are available (Becker and Ivashina (2015)). These regulatory ratings are then converted to NAIC designations using the mapping in Table IA-1 of the Supplementary Material. Data on bond par value outstanding are taken from Mergent's Fixed Income Securities Database, Lehman, and Datastream, as available in that order. We define MV to be the bond's market value, calculated as the par value outstanding times the market price of the bond per dollar of par.[10]

We retain return observations for corporate bonds traded in the U.S. with at least 1 year to maturity. We exclude observations for bonds with less than 1 year to maturity following Warga (1991) and Eom, Helwege, and Huang (2004), because these bonds are relatively illiquid. We further exclude mortgage-backed and asset-backed securities, equity-linked notes, convertible bonds, putable bonds, bonds with warrants, and bonds that are part of unit deals. We retain callable bonds, because they represent a significant portion of corporate bonds outstanding. Finally, we exclude bonds that are not U.S. dollar-denominated.

B. Bond Factors

We construct three corporate bond market factors. The first factor is designed to capture aggregate IG corporate bond market risk, which we refer to as bond market risk. Our proxy for this factor, CBMKT, is defined as the MV-weighted average excess return of the IG bonds in our return data. During 1993–2014, the period examined in our tests of H1 and H2, CBMKT generates an average excess return of 0.35% per month, with a standard deviation of 1.28%.

[8] In Section IA-II and Tables IA-2–IA-6 of the Supplementary Material, we demonstrate that our results hold when we exclude returns based on Lehman matrix prices from our sample.

[9] The 1-month U.S. Treasury bill return comes from Ken French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[10] Price data come from the database used to calculate the bond return.

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Fama and French (1993) and Gebhardt, Hvidkjær, and Swaminathan (2005) suggest that 2 sources of systematic risk impact corporate bond returns – a term factor driving risk associated with changes in interest rates for default risk-free bonds of different maturities, and a default factor related to changes in economic conditions that affect default probabilities and recovery rates. Following Jostova et al. (2013) and Becker and Ivashina (2015), we proxy for the term factor using TERM, defined as the return of the Barclays Long Maturity U.S. Treasury index (LHTRYLG) minus the return of the 1-month U.S. Treasury bill. During 1993–2014, TERM produces an average monthly excess return of 0.47%. We proxy for the default factor, DEF, with the component of CBMKT that is orthogonal to TERM. Assuming that U.S. Treasury securities are default risk-free, any covariation between CBMKT and TERM must be due to term-factor exposure. Defining DEF to be orthogonal to TERM, therefore, ensures that DEF has zero exposure to term risk. If, as suggested by Fama and French (1993) and Gebhardt et al. (2005), corporate bond market returns are driven by exposure to term and default factors, DEF can be considered a pure default factor. If factors other than term and default play a role, then DEF can be interpreted as absorbing the variation in corporate bond returns driven by all factors other than the term factor. The average excess return of DEF during 1993–2014 is 0.21% per month, which is notably smaller than that of TERM.[11]

In addition to the clean economic interpretation of TERM and DEF, defining DEF as the component of CBMKT that is orthogonal to TERM has several empirical advantages. First, since CBMKT is constructed from the bonds in our return data, our definitions of TERM and DEF ensure that these factors span the bonds' aggregate returns. Second, our methodology does not make any assumptions about the aggregate corporate bond market's exposure to term risk. This contrasts with the commonly used approach of proxying for the default factor with the returns of a zero-cost long–short portfolio that is long a portfolio of corporate bonds and short a portfolio of long-maturity U.S. Treasuries (see Fama and French (1993), Acharya, Amihud, and Bharath (2013), Chordia et al. (2017), Choi and Kim (2018), and Bai, Bali, and Wen (2019)), which implicitly assumes that the term-factor exposure of both the long and short portfolios is the same.[12] Indeed, our analysis suggests that the exposure of the aggregate bond market to term risk is only about 0.30. Thus, if we were to take DEF to be the difference between CBMKT and TERM, although TERM and DEF would still span the aggregate returns of the bonds in our data, our DEF factor would have a strong negative (−0.70) exposure to TERM, which would complicate the economic interpretation of our results.[13]

[11]The mean monthly excess DEF return is the intercept coefficient from a regression of CBMKT on TERM using data from 1993–2014. We present additional summary statistics for the monthly factor excess returns in Section IA-III and Table IA-7 of the Supplementary Material.

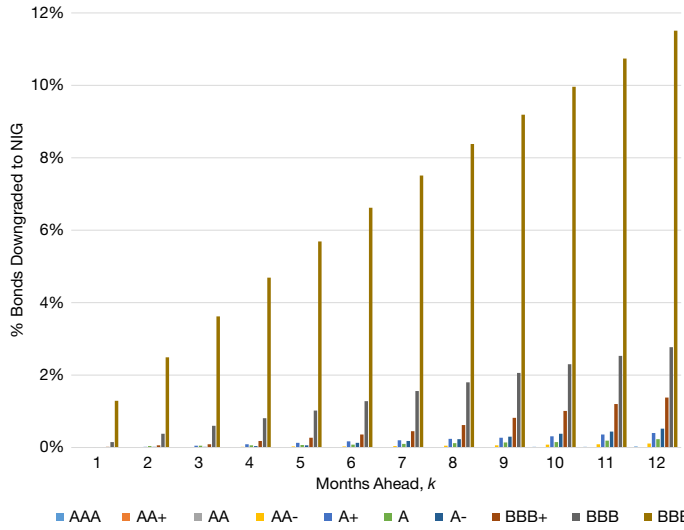
[12]If the term-factor exposures of the long and short portfolios are different, then the zero-cost portfolio has exposure to term risk and is, therefore, likely to be correlated with TERM.

[13]Since both methodologies define DEF as a linear combination of TERM and CBMKT, the space spanned by TERM and DEF together is the same in both cases. Thus, factor regressions that include TERM and DEF as independent variables will produce the exact same point estimate and inferential statistics for the intercept coefficient (alpha or risk-adjusted returns) in both cases. Default beta estimated from a regression of excess bond returns on TERM and DEF will also be the same regardless of the DEF

FIGURE 2

Noninvestment-Grade Downgrades by Regulatory Rating

Figure 2 presents the average percentage of bonds, by regulatory rating, that are downgraded to noninvestment-grade (NIG). A bond's regulatory rating is its credit rating for regulatory capital purposes. At the end of each month t, we group bonds according to their regulatory rating. For each group, we calculate the percentage of bonds that are downgraded to an NIG rating at some point in months $t+1$ through $t+k$, for $k \in \{1,2,\ldots,12\}$. The figure shows the time-series averages of the percentages of bonds downgraded to NIG from each regulatory rating and for each value of k. The analysis of k-month-ahead downgrades covers initial rating months t from Dec. 1992 to k months prior to Dec. 2014, inclusive.



Nonetheless, in Section IA-IV and Tables IA-8–IA-18 of the Supplementary Material, we perform several robustness tests to ensure that our results do not depend on our factor definitions.

C. Proximity to NIG

NIG proximity is intended to capture the possibility that a bond is downgraded to NIG. Figure 2 shows that over horizons of 1–12 months, bonds rated BBB−, the worst-rated NAIC designation 2 bonds, are downgraded to NIG much more often than bonds with any other IG rating. For instance, BBB− bonds are downgraded to NIG in the following month 8 times more often than BBB bonds. Therefore, we take bonds with a BBB− regulatory rating to be bonds with high NIG proximity.[14]

definition used, since the slope coefficient on DEF measures the covariance between the bond's excess return and the component of DEF that is orthogonal to TERM, which in both cases is simply the component of CBMKT that is orthogonal to TERM. However, the slope coefficient on TERM from such regressions will differ for different definitions of DEF.

[14]Our use of a BBB− rating as a proxy for high NIG proximity is further supported by the finding of Ellul et al. (2011) that three-quarters of the NIG downgrades they analyze are downgrades from BBB−.

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D. Systematic Risk Exposure

We measure bonds' systematic risk exposure (beta) to the 3 bond factors described in Section III.B: bond market risk, systematic term risk, and systematic default risk. The bond market beta of each bond is estimated from a regression of excess bond returns on CBMKT:

$$R_{i,t} = \beta_i^0 + \beta_i^{\text{CBMKT}} \text{CBMKT}_t + \varepsilon_{i,t}. \tag{2}$$

We take the estimated slope coefficient on CBMKT, β_i^{CBMKT}, as our measure of the bond's ex ante bond market beta. Term and default betas are estimated from a multivariate regression of excess bond returns on TERM and DEF:

$$R_{i,t} = \beta_i^0 + \beta_i^{\text{TERM}} \text{TERM}_t + \beta_i^{\text{DEF}} \text{DEF}_t + v_{i,t}. \tag{3}$$

We take the estimated slope coefficients β_i^{TERM} and β_i^{DEF} as our measures of the bond's ex ante term and default factor betas, respectively.[15] We calculate β^{CBMKT}, β^{TERM}, and β^{DEF} for each bond i at the end of each month t using a 60-month rolling window covering months $t-59$ through t, inclusive. To reduce measurement error, we follow Gebhardt et al. (2005) and require a minimum of 24 observations during the 60-month estimation window. Betas for bond–month observations not satisfying this criterion are considered missing.

E. Sample

The sample we use to test our hypotheses contains all observations in our return data for which the variables necessary to execute our tests are available. Specifically, the sample constructed at the end of each month t, used to examine month $t+1$ returns, contains all IG bonds with at least 1 year to maturity and available values of MV, β^{CBMKT}, β^{TERM}, and β^{DEF}. During the 1993–2014 period when rating-based capital requirements are in effect, the sample contains 3,405 bonds in the average month. Panel A of Table 1 presents the time-series averages of monthly cross-sectional summary statistics for these bonds. The mean (median) bond has β^{CBMKT} of 1.13 (1.10), β^{TERM} of 0.51 (0.49), and β^{DEF} of 0.84 (0.77). The mean (median) MV is \$215 (\$94) million. Month $t+1$ bond excess returns (R_{t+1}) are on average (in median) 0.39% (0.33%) per month with a cross-sectional standard deviation of 1.54%. Panel B shows the percentage of bonds by NAIC designation with BBB− bonds reported separately. Sixty-two percent of the bonds in our sample have an NAIC designation of 1. Bonds rated BBB−, which we consider to have high NIG proximity, are 9% of the sample bonds.

The time-series averages of the cross-sectional correlations between each pair of variables are shown in Panel C of Table 1. In the average month, the cross-sectional correlation between β^{CBMKT} and β^{TERM} is 0.80. This high correlation is not surprising given the 0.67 correlation between CBMKT and TERM (Table IA-7 in the Supplementary Material). In contrast, the correlation between β^{DEF} and β^{CBMKT} is much lower (0.37), and that between β^{DEF} and β^{TERM} is close to zero (−0.05).

[15] Gebhardt et al. (2005) demonstrate that betas estimated from regressions are more closely related to corporate-bond returns than bond characteristics that proxy for these betas (e.g., rating and duration).

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TABLE 1

Bond Summary Statistics

Table 1 presents summary statistics for the bonds in our sample. β^{CBMKT} is the slope coefficient from a regression of excess bond returns on CBMKT. β^{TERM} and β^{DEF} are the slope coefficients on TERM and DEF, respectively, from a regression of excess bond returns on TERM and DEF. The regressions used to calculate month t values of β^{CBMKT}, β^{TERM}, and β^{DEF} are fit using data from months $t-59$ to t, inclusive. MV is the par value outstanding times the market price of the bond per dollar of par, recorded in million dollars. β^{CBMKT}, β^{TERM}, β^{DEF}, and MV are measured at the end of month t. R_{t+1} is the excess bond return in month $t+1$, defined as the bond return minus the 1-month U.S. Treasury bill return, recorded as a percentage. Panel A shows the time-series averages of the monthly cross-sectional mean (Mean), standard deviation (SD), 25th percentile (25%), median (Median), and 75th percentile (75%) for each variable. Panel B shows the time-series average of the monthly cross-sectional percentage of bonds with National Association of Insurance Commissioners (NAIC) designation 1 (NAIC 1), bonds with NAIC designation 2 that are not rated BBB− (NAIC 2 No BBB−), and bonds rated BBB− (BBB−). Panel C shows the time-series averages of monthly cross-sectional Pearson product-moment correlations between β^{CBMKT}, β^{TERM}, β^{DEF}, and MV. Each variable is winsorized at the 0.5% and 99.5% levels on a monthly basis prior to calculating the cross-sectional correlations. The summary statistics, NAIC designations, and correlations cover sample formation (return) months t ($t+1$) from Dec. 1992 (Jan. 1993) to Nov. (Dec.) 2014, inclusive.

Panel A. Summary Statistics

Variable	Mean	SD	25%	Median	75%
β^{CBMKT}	1.13	0.47	0.80	1.10	1.44
β^{TERM}	0.51	0.24	0.35	0.49	0.66
β^{DEF}	0.84	0.65	0.44	0.77	1.15
MV	215	451	23	94	257
R_{t+1}	0.39	1.54	−0.24	0.33	0.96

Panel B. NAIC Designation Groups

NAIC 1	NAIC 2 No BBB−	BBB−
62.50%	28.46%	9.04%

Panel C. Correlations

	β^{TERM}	β^{DEF}	MV
β^{CBMKT}	0.80	0.37	0.05
β^{TERM}		−0.05	−0.06
β^{DEF}			0.24

MV has a positive cross-sectional correlation of 0.24 with β^{DEF} and close to zero correlation with each of β^{CBMKT} and β^{TERM}.

IV. Bond Pricing

In this section, we test our bond-pricing hypotheses H1 and H2. We focus on the 1993–2014 period, during which rating-based capital requirements for insurers are in effect.

A. NIG Proximity and Bond Pricing

We first test H1 by investigating whether a portfolio of bonds rated BBB−, which as we discuss in Section III.C have high NIG proximity, generates positive risk-adjusted returns. Furthermore, to ensure that any outperformance we document is specific to high-NIG proximity bonds, we examine the risk-adjusted performance of portfolios of better-rated bonds, as well as that of portfolios that are long BBB− bonds and short better-rated bonds.

Specifically, at the end of each month t, we form 5 portfolios. The first through fourth portfolios contain all bonds with an NAIC designation of 1 (NAIC 1), all bonds with an NAIC designation of 2 not rated BBB− (NAIC 2 No BBB−), all IG bonds not rated BBB− (IG No BBB−), and bonds rated BBB. The last portfolio contains

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only bonds rated BBB−. We then calculate the MV-weighted month $t+1$ excess returns for each portfolio, as well as for zero-cost long–short portfolios that are long the BBB− portfolio and short one of the other 4 portfolios. The result is a time series of monthly excess returns for each portfolio, including the long–short portfolios.

To measure risk-adjusted portfolio performance, we regress the time series of excess portfolio returns on the excess returns of factor-mimicking portfolios. The regressions are of the form:

$$R_{p,t+1} = \alpha_p + \boldsymbol{\beta}^{\mathbf{F}}_{\mathbf{post,p}} \mathbf{F_{t+1}} + \varepsilon_{p,t+1}, \tag{4}$$

where $R_{p,t+1}$ is portfolio p's postformation excess return, $\mathbf{F_{t+1}}$ is a vector of month $t+1$ factor-mimicking portfolio excess returns, and $\boldsymbol{\beta}^{\mathbf{F}}_{\mathbf{post,p}}$ is a vector of coefficients measuring the postformation exposures of the portfolio to the factors in $\mathbf{F_{t+1}}$. The estimated intercept α_p measures the portfolio's risk-adjusted return (alpha), where the risk adjustment reflects expected returns under a frictionless benchmark. A positive (negative) [zero] alpha indicates that the prices of the bonds in the portfolio are, on average, below (above) [the same as] the frictionless benchmark.

Although previous research focuses on term and default factors as the main drivers of corporate bond returns, Fama and French (1993) show that some corporate bonds have exposure to stock market factors as well. Therefore, in addition to TERM and DEF, we also include several stock return-based factors in $\mathbf{F_{t+1}}$. Specifically, we include the excess return on the aggregate U.S. stock market (STOCKMKT), the size (SMB) and value (HML) factors of Fama and French (1993), a momentum factor (MOM) motivated by Carhart (1997), and the traded liquidity factor (LIQ) of Pastor and Stambaugh (2003).[16] Since TERM and DEF are pure bond factor-mimicking portfolios, we orthogonalize each of STOCKMKT, SMB, HML, MOM, and LIQ with respect to TERM and DEF prior to running the factor regression.[17] In Sections IA-V–IA-VII and Tables IA-19–IA-31 of the Supplementary Material, we demonstrate that our results from this and subsequent sections are robust when using alternative factor models or augmenting our baseline factor model with a bond liquidity factor.

The results of the portfolio analyses, shown in Table 2, strongly support H1. The BBB− portfolio generates an alpha of 0.13% per month (t-statistic = 3.07). The alphas of the NAIC 1, NAIC 2 No BBB−, and IG No BBB− portfolios are small and statistically insignificant, suggesting that the pricing of these bonds is consistent with their frictionless benchmark. The BBB portfolio generates a marginally significant alpha of 0.05% per month (t-statistic = 1.67), perhaps due to the

[16]Monthly STOCKMKT, SMB, HML, and MOM values come from Ken French's website. Monthly LIQ values are for the traded liquidity factor from Lubos Pastor's website (http://faculty.chicagobooth.edu/lubos.pastor). SMB, HML, MOM, and LIQ are the excess returns of portfolios that are long (short) stocks with low (high) market capitalization, high (low) book-to-market ratio, high (low) momentum, and high (low) return sensitivity to aggregate liquidity, respectively.

[17]This orthogonalization does not affect the estimate of α_p or its statistical significance, but it ensures that $\beta^{\text{TERM}}_{post,p}$ and $\beta^{\text{DEF}}_{post,p}$ accurately measure the portfolio's postformation exposures to term and default factor risk, respectively. Another ramification of orthogonalizing STOCKMKT, SMB, HML, MOM, and LIQ to TERM and DEF is that the estimated coefficients $\beta^{\text{TERM}}_{post,p}$ and $\beta^{\text{DEF}}_{post,p}$, and their inferential statistics, are exactly the same as those that would have resulted from estimating a 2-factor model with TERM and DEF as the factors, which is how we estimate the ex ante values of β^{TERM} and β^{DEF} (see equation (3)).

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TABLE 2

Performance of Portfolios Sorted on Noninvestment-Grade Proximity (1993–2014)

Table 2 presents the results of a portfolio analysis examining the performance of portfolios formed by sorting on noninvestment-grade (NIG) proximity. At the end of each month t, all bonds are sorted into 5 portfolios based on whether they have i) a National Association of Insurance Commissioners (NAIC) designation of 1 (NAIC 1), ii) an NAIC designation of 2 but not a BBB− rating (NAIC 2 No BBB−), iii) an investment-grade (IG) rating but not a BBB− rating (IG No BBB−), iv) a BBB rating (BBB), or v) a BBB− rating (BBB−). We then calculate the market value–weighted month $t+1$ excess return of each portfolio, as well as that of zero-cost long–short portfolios that are long the BBB− portfolio and short each of the other 4 portfolios. The row labeled Excess return presents the time-series average of the monthly excess returns for each portfolio. The remainder of the table presents alphas and postformation factor sensitivities for each portfolio, calculated by regressing excess portfolio returns on TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ. We orthogonalize STOCKMKT, SMB, HML, MOM, and LIQ to TERM and DEF prior to running the regression. t-statistics, adjusted following Newey and West (1987) using 3 lags and testing the null hypothesis of a zero-mean excess return, alpha, or factor sensitivity, are shown in parentheses. Excess returns and alphas are in percentage per month. The analysis covers portfolio formation (return) months t ($t+1$) from Dec. 1992 (Jan. 1993) to Nov. (Dec.) 2014, inclusive.

Value	NAIC 1	NAIC 2 No BBB−	IG No BBB−	BBB	BBB−	[BBB−]−NAIC 1	[BBB−]−NAIC 2 No BBB−	[BBB−]−IG No BBB−	[BBB−]−BBB
Excess return	0.32 (4.14)	0.38 (4.65)	0.34 (4.39)	0.40 (4.88)	0.48 (5.71)	0.16 (3.24)	0.11 (2.71)	0.14 (3.35)	0.08 (2.06)
α	−0.01 (−0.45)	0.02 (0.67)	−0.00 (−0.17)	0.05 (1.67)	0.13 (3.07)	0.14 (2.86)	0.12 (2.92)	0.14 (3.14)	0.09 (2.10)
β_{post}^{TERM}	0.30 (15.34)	0.30 (13.58)	0.30 (15.11)	0.29 (13.07)	0.23 (8.94)	−0.07 (−4.21)	−0.06 (−4.84)	−0.07 (−4.51)	−0.06 (−4.18)
β_{post}^{DEF}	0.90 (47.21)	0.97 (37.55)	0.93 (67.76)	0.99 (37.64)	1.05 (24.45)	0.14 (2.89)	0.08 (2.08)	0.12 (2.80)	0.06 (1.42)
$\beta_{post}^{STOCKMKT}$	−0.02 (−3.49)	0.01 (0.99)	−0.01 (−1.84)	−0.01 (−1.39)	0.02 (1.37)	0.03 (2.53)	0.01 (0.85)	0.02 (1.97)	0.03 (2.30)
β_{post}^{SMB}	0.00 (0.80)	0.01 (0.64)	0.01 (1.22)	0.00 (0.23)	0.00 (0.24)	−0.00 (−0.09)	−0.00 (−0.16)	−0.00 (−0.15)	0.00 (0.11)
β_{post}^{HML}	−0.00 (−0.33)	0.01 (1.49)	0.00 (0.73)	−0.00 (−0.17)	−0.01 (−0.60)	−0.01 (−0.40)	−0.02 (−1.64)	−0.01 (−0.84)	−0.01 (−0.51)
β_{post}^{MOM}	0.01 (2.25)	−0.00 (−0.33)	0.00 (1.31)	0.00 (0.88)	−0.01 (−0.70)	−0.01 (−1.47)	−0.00 (−0.54)	−0.01 (−1.12)	−0.01 (−1.28)
β_{post}^{LIQ}	−0.01 (−2.09)	0.01 (1.89)	−0.00 (−0.19)	0.01 (1.04)	0.02 (2.18)	0.03 (2.70)	0.01 (1.14)	0.02 (2.25)	0.02 (1.58)

moderately high NIG proximity of BBB bonds. The long–short portfolios all generate a positive and highly statistically significant alpha. The portfolio that is long BBB− bonds and short NAIC designation 1 bonds ([BBB−]−NAIC 1) generates an alpha of 0.14% per month (t-statistic = 2.86). The portfolios that are long bonds rated BBB− and short either all other NAIC designation 2 bonds ([BBB−]−NAIC 2 No BBB−) or all other IG bonds ([BBB−]−IG No BBB−) produce similar results. The BBB− portfolio even outperforms the portfolio of bonds rated BBB ([BBB−]−BBB) by 0.09% per month (t-statistic = 2.10).[18] Consistent with ratings measuring idiosyncratic but not systematic risk (Iannotta et al. (2019)), the long–short portfolios have economically small and, in most cases, statistically insignificant postformation risk-factor exposure.[19]

[18]This finding indicates that insurers forego 0.09% of alpha per month to decrease the probability of a downgrade to NIG in the next month by 0.0114 (i.e., the difference in the rate of downgrades to NIG for bonds rated BBB− and BBB from Figure 2). Thus, insurers seem to perceive the cost of holding a bond with high NIG proximity as greater than 7.89% (0.09%/0.0114). This estimate of the cost is similar in magnitude to that in Ellul et al. (2011), who find that insurers fire-sell bonds downgraded to NIG at a median price that is 6.83% below the bonds' fair value.

[19]The financial crisis of 2007–2009 was a period characterized by a large number of credit rating downgrades and substantial price volatility in fixed-income markets. To ensure that our results are not

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We conduct several additional portfolio analyses to assess whether NIG proximity is behind the effect we document and whether a similar effect exists around the threshold between NAIC designations 1 and 2. First, we show that among bonds with a BBB− regulatory rating, the outperformance is stronger among bonds that have higher NIG proximity. These tests take bonds rated NIG by one CRP (Section IA-IX.A and Table IA-36 of the Supplementary Material) and bonds with downward rating momentum (Lando and Skødeberg (2002), Section IA-IX.B and Table IA-37 of the Supplementary Material) as having higher NIG proximity than other bonds with BBB− regulatory ratings. Second, in Section IA-IX.C and Table IA-38 of the Supplementary Material, we show that portfolios that are long bonds rated BBB (the second highest NIG proximity rating) and short better-rated bonds generate positive but economically small and statistically weak risk-adjusted returns. Finally, consistent with Becker and Ivashina's (2015) finding that insurers investment behavior is not affected by the increase in required capital charge from NAIC designation 1 to NAIC designation 2, in Section IA-IX.D and Table IA-39 of the Supplementary Material, we find no evidence that the prices of bonds rated A− (the lowest NAIC 1 designation rating) deviate from the frictionless benchmark.

B. Systematic Risk Exposure and Bond Pricing

We test H2 by conducting conditional portfolio analyses. Specifically, at the end of each month t, we first separate bonds into 2 groups based on their NAIC designation and then, within each group, we sort bonds into decile portfolios based on an ascending ordering of one of our risk-factor exposure measures (β^{CBMKT}, β^{TERM}, or β^{DEF}). We next calculate the MV-weighted month $t+1$ excess returns for each portfolio as well as for the zero-cost long–short portfolio that is long the decile 10 portfolio and short the decile 1 portfolio in each NAIC designation group. Finally, we calculate monthly excess returns in each systematic risk decile portfolio for the average NAIC designation group by averaging the excess returns of the given systematic risk decile portfolio (including the long–short portfolio) across the 2 NAIC designation groups, and examine the performance of these portfolios. These excess returns, which are the focus of our analyses, reflect the performance of portfolios constructed to be neutral to capital charge while having dispersion in risk-factor exposure.

Our first test of the relation between bond pricing and systematic risk exposure examines the performance of portfolios constructed using β^{CBMKT} as the measure of systematic risk exposure. The results of this test are presented in Table 3. The objective of sorting on β^{CBMKT}, which is measured using data from the period prior to portfolio formation, is to generate a set of portfolios that have strong postformation dispersion in bond market risk exposure. To ensure that our portfolios satisfy this criterion, we perform time-series regressions of each portfolio's excess returns on CBMKT.[20] The slope coefficients from these regressions, reported in the rows

driven by the events of this period, in Section IA-VIII and Tables IA-32–IA-35 of the Supplementary Material, we remove the financial crisis period from our sample and repeat our main bond-pricing tests. The results are qualitatively unchanged.

[20]We estimate postformation exposure to CBMKT using the 1-factor model given by equation (2), because CBMKT is not one of the factors in the model we use to evaluate risk-adjusted performance

TABLE 3

Performance of Portfolios Sorted on $\beta^{CBMKT}\beta^{TERM}$, or β^{DEF}(1993–2014)

Table 3 presents the results of analyses examining the performance of portfolios formed by sorting on β^{CBMKT}, β^{TERM}, or β^{DEF}, conditional on National Association of Insurance Commissioners (NAIC) designation. At the end of each month t, all bonds are sorted into 2 groups, NAIC designation 1 (NAIC 1) and NAIC designation 2 (NAIC 2). All bonds in each group are then sorted into decile portfolios based on an ascending ordering of β^{CBMKT}, β^{TERM}, or β^{DEF}. We then calculate the market value–weighted month $t+1$ excess return of each portfolio, as well as that of a zero-cost long–short portfolio that is long the decile 10 portfolio and short the decile 1 portfolio in each NAIC designation group. Finally, for each decile portfolio as well as the long–short portfolio, we calculate the average excess return across the 2 NAIC designation groups. The row labeled β^{CBMKT}_{post} presents the slope coefficient from a regression of excess portfolio returns on CBMKT. The rows labeled β^{TERM}_{post} and β^{DEF}_{post} present the slope coefficients on TERM and DEF, respectively, from a regression of excess portfolio returns on TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ. The rows labeled Excess return present the time-series average of the monthly excess returns. The rows labeled α present portfolio alphas, calculated by regressing excess portfolio returns on TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ. t-statistics, adjusted following Newey and West (1987) using 3 lags and testing the null hypothesis of a zero postformation exposure to bond market risk, mean excess return, or alpha, are shown in parentheses. Excess returns and alphas are in percentage per month. The analysis covers portfolio formation (return) months t ($t+1$) from Dec. 1992 (Jan. 1993) to Nov. (Dec.) 2014, inclusive.

Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	10–1
β^{CBMKT}	β^{CBMKT}_{post}	0.36	0.54	0.64	0.74	0.78	0.96	1.03	1.19	1.39	1.66	1.29
		(19.17)	(20.89)	(26.68)	(30.45)	(32.40)	(43.97)	(37.84)	(47.69)	(47.59)	(48.87)	(28.79)
	Excess return	0.34	0.25	0.28	0.28	0.25	0.36	0.41	0.42	0.47	0.51	0.16
		(9.15)	(4.72)	(4.78)	(4.22)	(3.71)	(4.43)	(4.62)	(4.24)	(4.04)	(3.67)	(1.39)
	α	0.23	0.06	0.06	0.01	–0.02	0.01	0.05	–0.01	–0.03	–0.12	–0.35
		(9.26)	(1.86)	(1.83)	(0.30)	(–0.50)	(0.38)	(1.21)	(–0.17)	(–0.75)	(–2.85)	(–6.30)
β^{TERM}	β^{TERM}_{post}	0.08	0.14	0.18	0.20	0.25	0.30	0.35	0.42	0.52	0.66	0.58
		(3.85)	(8.21)	(9.94)	(10.18)	(12.05)	(12.55)	(14.71)	(15.79)	(17.68)	(21.82)	(25.78)
	Excess return	0.37	0.33	0.29	0.30	0.32	0.38	0.35	0.43	0.45	0.49	0.11
		(6.47)	(6.00)	(4.90)	(4.41)	(4.44)	(4.41)	(3.88)	(4.08)	(3.63)	(3.38)	(0.93)
	α	0.21	0.12	0.05	0.04	0.02	0.01	–0.04	–0.02	–0.10	–0.13	–0.34
		(6.26)	(4.02)	(1.63)	(1.05)	(0.75)	(0.25)	(–1.13)	(–0.42)	(–2.51)	(–2.79)	(–5.77)
β^{DEF}	β^{DEF}_{post}	0.67	0.64	0.73	0.70	0.76	0.79	0.85	0.96	1.10	1.37	0.70
		(16.41)	(16.85)	(21.52)	(20.56)	(26.98)	(27.93)	(34.29)	(30.67)	(35.78)	(34.49)	(10.13)
	Excess return	0.39	0.31	0.32	0.28	0.30	0.30	0.35	0.37	0.44	0.48	0.09
		(5.28)	(4.37)	(4.47)	(4.07)	(4.34)	(4.15)	(4.71)	(4.40)	(4.92)	(4.44)	(1.21)
	α	0.09	0.02	0.03	0.00	0.01	0.00	0.04	0.04	0.06	0.01	–0.08
		(2.24)	(0.47)	(0.83)	(0.09)	(0.48)	(0.13)	(1.56)	(1.33)	(1.83)	(0.36)	(–1.11)

labeled β^{CBMKT}_{post}, demonstrate that our portfolio formation procedure works as intended. The postformation exposures to CBMKT increase monotonically from 0.36 for the decile 1 portfolio to 1.66 for the decile 10 portfolio. The portfolio that is long bonds in the highest β^{CBMKT} decile and short bonds in the lowest β^{CBMKT} decile has a postformation exposure to CBMKT of 1.29 (t-statistic = 28.79). Consistent with the increasing pattern in bond market risk exposure, the average excess returns of the portfolios generally increase across the β^{CBMKT} deciles. This is important because it suggests that insurers can indeed increase the expected return of their portfolio by tilting their holdings toward bonds with high systematic risk exposure. However, although the average excess return of the long–short β^{CBMKT} portfolio is positive, it is statistically insignificant.

(equation (4)). Since by construction CBMKT is a linear combination of TERM and DEF, including CBMKT in equation (4) would introduce multicollinearity. If we were to replace TERM and DEF with CBMKT in equation (4) and orthogonalize STOCKMKT, SMB, HML, MOM, and LIQ with respect to CBMKT, the estimate of postformation exposure would be the same as the one obtained from the 1-factor model.

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Most importantly, in support of H2, the results in Table 3 provide strong evidence that bonds with high (low) CBMKT exposure generate low (high) risk-adjusted returns. Alphas, measured using the factor model given by equation (4) and shown in the rows labeled α, generally decrease across the β^{CBMKT} decile portfolios. The decile 1 portfolio generates a significantly positive alpha of 0.23% per month (t-statistic = 9.26), and the decile 10 portfolio generates a significantly negative alpha of −0.12% per month (t-statistic = −2.85).[21] The long–short β^{CBMKT} portfolio generates a monthly alpha of −0.35% (t-statistic = −6.30), which is both economically large and highly statistically significant.

We next examine the performance of portfolios constructed using β^{TERM} as the measure of systematic risk exposure. The results in Table 3 strongly support our hypothesis that bonds with high (low) term-factor exposure generate negative (positive) risk-adjusted returns. The decile 1 portfolio generates significantly positive alpha, whereas the decile 10 portfolio generates significantly negative alpha. The long–short β^{TERM} portfolio generates monthly alpha of −0.34% (t-statistic = −5.77). The portfolios' postformation exposures to TERM, measured using the factor model given by equation (4), demonstrate that the test design successfully achieves its objective of producing portfolios with strong postformation dispersion in term-factor exposure. $\beta^{\text{TERM}}_{\text{post}}$ increases monotonically across the β^{TERM} deciles, and the long–short portfolio has large and highly statistically significant positive $\beta^{\text{TERM}}_{\text{post}}$.

Finally, we examine the risk-adjusted returns of portfolios formed by sorting on β^{DEF}. Table 3 shows that β^{DEF} portfolios have generally increasing postformation exposure to default factor risk, and the long–short portfolio has an economically large and statistically significant positive $\beta^{\text{DEF}}_{\text{post}}$. The alpha of the decile 1 portfolio is statistically positive, but small, whereas that of the decile 10 portfolio is statistically indistinguishable from zero. The alpha of the long–short β^{DEF} portfolio is negative but also statistically insignificant. The results suggest that if there is a negative relation between default factor exposure and risk-adjusted bond returns, it is economically weak. A potential explanation for this finding is that insurers have a strong preference for systematic term risk but not for systematic default risk, because the premium for systematic term risk is larger than that for systematic default risk (see Table IA-7 in the Supplementary Material). Analysis of insurer holdings in Section V.A.1 supports this conjecture.

C. Yields

Throughout this article, we test our bond-pricing hypotheses using the well-established practice in the empirical asset-pricing literature of estimating alphas from factor regressions of ex post realized returns. Some studies, however, test for patterns in bond prices by analyzing yields instead of returns. Motivated by these studies, we use an alternative empirical approach that examines risk-adjusted yields, and again find evidence consistent with our bond-pricing hypotheses. We choose not to present the results from these analyses, because we cannot properly

[21] To conserve space, in the main article, we present only the estimates of α from the factor regressions. The full set of estimated coefficients for each portfolio are discussed in Section IA-X and shown in Tables IA-40–IA-42 of the Supplementary Material.

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account for expected default losses when calculating risk-adjusted yields, but the results are available from us upon request.

D. Persistence of Pricing Effects

Although the effects on the real economy of transient alpha generated by temporary price pressure are minimal, those of persistent alpha can be substantial (Stein (1996), Chirinko and Schaller (2001), Baker, Stein, and Wurgler (2003), Gilchrist, Himmelberg, and Huberman (2005), Polk and Sapienza (2009), Harford, Martos-Vila, and Rhodes-Kropf (2015), and Warusawitharana and Whited (2016)). Therefore, we test whether the price patterns we detect are temporary or whether they reflect a persistent equilibrium that diverges from the frictionless benchmark by examining the performance of the portfolios for a year after they are created. Specifically, we repeat the analyses described in Sections IVA and IVB, except that now we analyze the performance of the portfolios k months after they are formed, for $k \in \{2, \ldots, 12\}$. The results of these analyses, shown in Table 4, demonstrate that the pricing effects we document are highly persistent. To save space, for rating-sorted portfolios, we only present results for the BBB− and long–short portfolios, and for portfolios sorted on systematic risk exposure, we only present results for the decile 1, decile 10, and long–short portfolios. The BBB− portfolio and portfolios that are long bonds rated BBB− and short other sets of IG bonds all generate positive and highly significant alphas for at least 12 months after portfolio formation, with one exception: The alphas of the [BBB−]−BBB portfolios are marginally significant from $t+7$ onward. For portfolios sorted on β^{CBMKT} or β^{TERM}, the alphas of the decile 1 portfolio are all positive and significant, and those of the decile 10 portfolio and the long–short portfolios are all negative and significant. The alphas of the β^{DEF} portfolios are once again small and, in most cases, statistically insignificant. In addition to demonstrating that the pricing effects are highly persistent, the results in Table 4 address any concern that our findings are driven by microstructure effects arising from forming portfolios at the end of month t and assessing their performance in month $t+1$.

V. Drivers of Bond-Pricing Effects

Having found support for H1 and H2, we next investigate the drivers of the pricing patterns by testing H3, H4, and H5.

A. Insurer Demand and Bond Pricing

Our tests of H3 and H4 require data on insurers' corporate bond holdings, which we gather from insurers' statutory filings with the NAIC for the 2002–2014 period. Part 1 of Schedule D of each insurer's filing lists every bond the insurer held at calendar year-end. For each bond, we aggregate the par value held across all insurers in a given year. We then define %INS_HELD as the bond's par value held by all insurers scaled by the bond's contemporaneous par value outstanding expressed as a percentage. Since insurer holdings data from the NAIC are available at an annual frequency, %INS_HELD is calculated each December and remains the same through the following November. Moreover, since the data start in 2002, the

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TABLE 4

Persistence of Portfolio Performance (1993–2014)

Table 4 presents portfolio alphas calculated from returns in months 2–12 after portfolio formation. At the end of each month t, we form portfolios as described in Tables 2 and 3. We then calculate the excess returns of the portfolios in months $t+k$, for $k \in \{2,3,\ldots,12\}$. For each portfolio and each value of k, the table presents the intercept coefficient (alpha) from a regression of excess portfolio returns on TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ. t-statistics, adjusted following Newey and West (1987) using 3 lags and testing the null hypothesis of a zero alpha, are shown in parentheses. Alphas are in percentage per month. The analysis covers portfolio formation (return) months t ($t+k$) from k months prior to Jan. 1993 (Jan. 1993) to k months prior to Dec. 2014 (Dec. 2014), inclusive.

k	BBB−	[BBB−]−NAIC 1	[BBB−]−NAIC 2 No BBB−	[BBB−]−IG No BBB−	[BBB−]−BBB	β^{CBMKT} 1	β^{CBMKT} 10	β^{CBMKT} 10−1	β^{TERM} 1	β^{TERM} 10	β^{TERM} 10−1	β^{DEF} 1	β^{DEF} 10	β^{DEF} 10−1
2	0.15	0.16	0.13	0.15	0.11	0.22	–0.13	–0.35	0.22	–0.12	–0.34	0.07	–0.00	–0.07
	(3.40)	(3.29)	(3.12)	(3.46)	(2.43)	(9.17)	(–3.21)	(–6.63)	(6.36)	(–2.49)	(–5.54)	(1.67)	(–0.00)	(–0.99)
3	0.14	0.16	0.12	0.15	0.09	0.21	–0.12	–0.33	0.21	–0.13	–0.34	0.05	0.00	–0.05
	(3.22)	(3.15)	(2.84)	(3.25)	(2.02)	(8.98)	(–2.90)	(–6.16)	(6.35)	(–2.86)	(–5.81)	(1.20)	(0.07)	(–0.71)
4	0.16	0.18	0.14	0.17	0.12	0.21	–0.13	–0.34	0.21	–0.14	–0.35	0.06	0.00	–0.06
	(4.03)	(3.85)	(3.52)	(4.08)	(2.98)	(9.41)	(–3.10)	(–6.21)	(6.42)	(–2.96)	(–5.67)	(1.62)	(0.10)	(–0.91)
5	0.15	0.16	0.13	0.16	0.10	0.22	–0.15	–0.37	0.21	–0.14	–0.35	0.06	–0.00	–0.06
	(4.17)	(3.77)	(3.55)	(4.19)	(3.00)	(10.01)	(–3.56)	(–6.89)	(6.79)	(–2.99)	(–5.90)	(1.67)	(–0.01)	(–1.01)
6	0.14	0.14	0.11	0.14	0.08	0.21	–0.12	–0.33	0.20	–0.13	–0.33	0.06	0.01	–0.05
	(3.89)	(3.61)	(2.95)	(3.88)	(2.23)	(9.46)	(–2.70)	(–6.27)	(6.54)	(–2.96)	(–5.71)	(1.69)	(0.38)	(–0.83)
7	0.13	0.14	0.10	0.13	0.06	0.20	–0.12	–0.32	0.19	–0.13	–0.32	0.07	0.00	–0.07
	(3.84)	(3.56)	(2.75)	(3.78)	(1.78)	(8.71)	(–2.72)	(–5.94)	(6.34)	(–2.86)	(–5.50)	(2.00)	(0.11)	(–1.13)
8	0.12	0.13	0.10	0.12	0.06	0.21	–0.14	–0.35	0.19	–0.12	–0.32	0.07	–0.01	–0.08
	(3.59)	(3.37)	(2.63)	(3.51)	(1.63)	(8.70)	(–3.14)	(–6.37)	(6.24)	(–2.74)	(–5.37)	(2.20)	(–0.19)	(–1.44)
9	0.12	0.13	0.10	0.12	0.06	0.21	–0.13	–0.34	0.19	–0.13	–0.32	0.07	–0.01	–0.08
	(3.47)	(3.23)	(2.59)	(3.39)	(1.72)	(8.53)	(–2.95)	(–6.05)	(6.49)	(–2.75)	(–5.38)	(1.97)	(–0.34)	(–1.43)
10	0.11	0.12	0.09	0.11	0.06	0.22	–0.12	–0.33	0.19	–0.14	–0.33	0.09	–0.02	–0.11
	(3.41)	(3.22)	(2.53)	(3.35)	(1.73)	(9.27)	(–2.63)	(–5.88)	(6.37)	(–3.03)	(–5.53)	(2.65)	(–0.68)	(–2.01)
11	0.11	0.12	0.09	0.12	0.06	0.20	–0.12	–0.31	0.18	–0.13	–0.32	0.07	–0.00	–0.07
	(3.54)	(3.30)	(2.63)	(3.46)	(1.72)	(8.55)	(–2.58)	(–5.60)	(6.27)	(–2.92)	(–5.41)	(1.84)	(–0.02)	(–1.16)
12	0.11	0.12	0.09	0.11	0.06	0.19	–0.12	–0.31	0.16	–0.14	–0.30	0.07	0.01	–0.06
	(3.46)	(3.22)	(2.69)	(3.33)	(1.72)	(8.58)	(–2.74)	(–5.90)	(5.66)	(–3.13)	(–5.27)	(1.76)	(0.25)	(–1.00)

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analyses in this section cover months t (return months $t+1$) from Dec. 2002 (Jan. 2003) to Nov. (Dec.) 2014, inclusive.

1. Insurer Holdings

We first test H3 by examining whether insurers invest less in bonds with high NIG proximity and more (less) in bonds with high (low) systematic risk exposure, consistent with incentives created by rating-based capital requirements. We do so by estimating weighted least-squares (WLS) regressions, with MV as the weight, of %INS_HELD on NIG proximity (BBB− indicator) and systematic risk exposure (β^{CBMKT}, β^{TERM}, or β^{DEF}). We also control for the possibility that any detected pattern in insurer holdings is a function of a bond's NAIC designation (NAIC2 indicator). By using WLS regressions, we give equal weight to each dollar invested in the bond market, instead of equal weight to each bond as in OLS regressions. This alleviates the concern that insurers' investments in small bonds, which are a large portion of the number but a small portion of the market value of IG corporate bonds (see Panel A of Table 1), drive our results. The regressions are of the form:

$$\%\text{INS_HELD}_{i,t} = \gamma_0 + \gamma_{\text{BBB}-}\text{BBB}-_{i,t} + \gamma_{\beta^j}\beta^j_{i,t} + \gamma_{\text{NAIC2}}\text{NAIC2}_{i,t} + \omega_{i,t}, \quad (5)$$

where BBB− equals 1 if the bond is rated BBB− and 0 otherwise, β^j is either β^{CBMKT}, β^{TERM}, or β^{DEF}, and NAIC2 equals 1 for NAIC designation 2 bonds and 0 otherwise. Regression specification (5) is not intended to be a complete model of insurer corporate bond investment choices. The objective here is to simply test whether insurers' aggregate corporate bond portfolios do indeed overweight high-systematic risk bonds and underweight high-NIG proximity bonds.

We estimate the regression specification (5) in 2 ways. First, each month t we run cross-sectional bond-level regressions in the spirit of Fama and MacBeth (FM) (1973). We then report the time-series averages of the cross-sectional regression coefficients, and Newey and West (1987)-adjusted t-statistics testing the null hypothesis that the time-series average equals 0. The results of these regressions, presented in columns 1–3 of Table 5, provide strong evidence that insurers are averse to high-NIG proximity bonds and have a preference for bonds with high systematic risk exposure, albeit not default factor risk exposure. In all 3 specifications, the coefficient on BBB− is negative and highly statistically significant, ranging from −4.53 (t-statistic = −8.48) in specification (2) to −7.88 (t-statistic = −12.39) in specification (3). That is, insurers hold approximately 4–8 percentage points less of the outstanding par value of BBB− bonds than of other NAIC designation 2 bonds. The average coefficient of 10.03 (t-statistic = 13.04) on β^{CBMKT} in specification (1) indicates that a 1-standard-deviation increase of 0.47 (see Table 1) in bond market risk exposure is associated with insurers holding 4.71 (10.03×0.47) percentage points more of the outstanding par value of the bond. For term-factor exposure, the coefficient of 35.69 (t-statistic = 25.45) on β^{TERM} indicates an increase in holdings of 8.57 (35.69×0.24) percentage points per standard deviation increase of β^{TERM} (0.24). Finally, the analysis detects no significant relation between β^{DEF} and insurer holdings. This is not surprising given that the default risk premium is substantially smaller than the term risk premium among IG bonds (see Table IA-7 in the Supplementary Material), giving insurers less

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TABLE 5

Insurer Holdings Regressions (2003–2014)

Table 5 presents the results of weighted least-squares of Fama and MacBeth (FM) (1973) and panel regressions of insurer holdings on bond variables using MV as the weight. The dependent variable is %INS_HELD, calculated as the proportion of a bond's market value held by life and property/casualty insurers. BBB– is an indicator variable equal to 1 if the bond's rating is BBB–, and 0 otherwise. NAIC2 is an indicator variable equal to 1 if the bond's National Association of Insurance Commissioners (NAIC) designation is 2, and 0 otherwise. In columns labeled FM, we report the time-series averages of coefficients from monthly cross-sectional regressions, and *t*-statistics, adjusted following Newey and West (1987) using 3 lags and testing the null hypothesis that the time-series average of the estimated coefficient is 0, in parentheses. In columns labeled Panel, we report coefficients from panel regressions with year fixed effects (FEs), and *t*-statistics that use standard errors clustered by letter rating and year in parentheses. The row labeled *N* presents the average number of observations used in the monthly cross-sectional regressions in columns 1–3 and the total number of observations in the panel regressions in columns 4–6. The analysis covers months *t* from Dec. 2002 to Nov. 2014, inclusive.

	FM	FM	FM	Panel	Panel	Panel
	1	2	3	4	5	6
BBB–	–7.06	–4.53	–7.88	–7.47	–4.54	–8.65
	(–13.77)	(–8.48)	(–12.39)	(–43.85)	(–12.98)	(–39.65)
β^{CBMKT}	10.03			7.81		
	(13.04)			(9.65)		
β^{TERM}		35.69			33.79	
		(25.45)			(18.15)	
β^{DEF}			–0.28			–0.25
			(–1.18)			(–0.32)
NAIC2	5.47	7.16	5.94	5.83	7.32	5.80
	(13.30)	(17.63)	(15.59)	(3.15)	(3.50)	(2.81)
Intercept	20.04	19.00	31.89			
	(44.05)	(34.93)	(39.98)			
Year FE				Yes	Yes	Yes
N	4,539	4,539	4,539	653,591	653,591	653,591

incentive to take default risk than term risk. If, as we will test in the next section, insurer demand drives the pricing patterns observed in Tables 2–4, the lack of a relation between β^{DEF} and insurer demand explains why we do not see a relation between β^{DEF} and risk-adjusted bond returns.

Second, to alleviate any concern that the persistence of %INS_HELD may result in correlated error terms and inflated *t*-statistics (Petersen (2009)), we estimate the regression in equation (5) as a panel regression with year fixed effects and standard errors clustered by year and rating. The results of these estimations, reported in columns 4–6 of Table 5, are similar to those of the FM regressions reported in columns 1–3.

2. Insurer Holdings and Bond Performance

Having demonstrated that insurers strongly tilt their corporate bond portfolios away from bonds with high NIG proximity and toward bonds with high systematic risk exposure, bond characteristics that our hypotheses link to investment incentives created by rating-based capital requirements, we next test H4 by examining the relation between insurer holdings and risk-adjusted bond returns. Although our hypothesis is that high (low) insurer demand causes high (low) bond prices and thus low (high) future risk-adjusted returns, our analysis is complicated by the possibility that insurer demand may also be a function of bond mispricing – insurers may be sophisticated investors who, in addition to the portfolio tilting that arises from incentives created by rating-based capital requirements, also overweight underpriced bonds. Our empirical tests, therefore, must be designed to measure the

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relation between future risk-adjusted returns and the component of insurers' demand that is not driven by alpha-seeking behavior.

Therefore, we examine the relation between insurer holdings and risk-adjusted returns of portfolios formed by sorting bonds on NIG proximity and systematic risk exposure. Specifically, at the end of each month t, we sort all NAIC designation 2 bonds into deciles based on an ascending ordering of β^{TERM}. We also separate the NAIC designation 2 bonds into those rated BBB− and those with any other rating. The intersections of the 10 β^{TERM} groups and the 2 NIG proximity (BBB− and NAIC 2 No BBB−) groups form the 20 portfolios whose MV-weighted month $t+1$ returns we examine. Since insurers have low (high) demand for bonds with high NIG proximity (high systematic risk exposure) and these bonds tend to generate high (low) risk-adjusted returns, it is unlikely that any relation between insurer holdings and bond performance across these portfolios is driven by alpha-seeking behavior. Indeed, alpha seeking by insurers would only serve as a deterrent for them to exhibit the demand patterns we have documented, thus potentially weakening the power of our tests. We focus on NAIC designation 2 bonds, because this allows us to hold capital charge constant while also allowing variation in NIG proximity, and we use β^{TERM} as our measure of systematic risk exposure, because the results in Table 5 indicate that insurers' demand for high-systematic risk bonds is particularly strong for bonds with high term factor risk exposure.

We next calculate the proportion held by insurers of the aggregate market value of all bonds in each of the 20 portfolios. Specifically, in any given month, we define portfolio-level %INS_HELD to be the MV-weighted average of bond-level %INS_HELD across all bonds in that portfolio. If, as we hypothesize, insurers' demand drives the pricing patterns documented in Section IV, then the alphas of the 20 portfolios should be negatively related to insurer holdings.[22]

We test the impact of insurer holdings on bond pricing in 2 ways.[23] First, we run a single regression of the 20 portfolio alphas on the corresponding average portfolio-level %INS_HELD. The results of this regression, shown in column 1 of Table 6, strongly suggest that the pricing patterns we document earlier in the article are driven by insurer demand, since the coefficient on the average portfolio-level %INS_HELD is negative and highly statistically significant. The adjusted R^2 value from the regression is 68.22%, indicating that most of the variation in portfolio alphas can be attributed to insurer demand.

Our second approach to examining the impact of insurer demand on corporate bond prices is to perform FM regression analyses of monthly portfolio-level alphas on monthly portfolio-level %INS_HELD for the 20 portfolios described earlier. We calculate the alpha for a portfolio in month $t+1$ by taking the portfolio's month $t+1$ excess return and subtracting from it the estimated factor sensitivities from

[22]In Section IA-XI and Table IA-43 of the Supplementary Material, we show that the 20 portfolios' alphas are consistent with the pricing patterns documented in Section IV and the proportions held by insurers are consistent with the results of the bond-level analysis discussed in Section V.A.1. In Section IA-XII and Table IA-44 of the Supplementary Material, we demonstrate that our results are robust when we form portfolios by using other groups of IG bonds or β^{CBMKT} as the measure of systematic risk exposure.

[23]These tests use portfolio-level observations to overcome noise associated with estimating alphas and risk-factor exposures for individual bond–month observations (Fama and MacBeth (1973)).

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TABLE 6

Insurer Holdings and Portfolio Alphas (2003–2014)

Table 6 presents the results from single and Fama and MacBeth (FM) (1973) regressions of portfolio alphas on insurer holdings for 20 β^{TERM} and rating-based portfolios. To form the portfolios, at the end of each month t, we sort all National Association of Insurance Commissioners (NAIC) designation 2 bonds into deciles based on an ascending ordering of β^{TERM}. We also separate the NAIC designation 2 bonds into those rated BBB− and those with any other rating. We use the intersections of the 10 β^{TERM} groups and the 2 rating-based (BBB− and NAIC 2 No BBB−) groups to form the 20 portfolios used in the regressions. The columns labeled Single present the results of a single cross-sectional regression of portfolio alpha on the time-series average of portfolio-level insurer holdings. The columns labeled FM present the time-series averages of the coefficients from monthly cross-sectional regressions of monthly portfolio alpha on monthly portfolio-level insurer holdings. Monthly portfolio alphas are calculated by taking the portfolio's excess return and subtracting the estimated factor sensitivities times the corresponding factor excess returns in the same month. %INS_HELD is calculated as the proportion of a bond's market value held by life and property/casualty insurers. $\%INS_HELD_{Constrained}$ and $\%INS_HELD_{Unconstrained}$ are calculated as the proportion of a bond's market value held by constrained and unconstrained, respectively, life and property/casualty insurers. t-statistics, testing the null hypothesis of a zero coefficient (Single) or average coefficient (FM, adjusted following Newey and West (1987) using 3 lags), are shown in parentheses. The row labeled N presents the number of observations used in the regressions in the columns labeled Single, and the number of observations used in each monthly cross-sectional regression in the columns labeled FM. The analysis covers portfolio formation (return) months t ($t+1$) from Dec. 2002 (Jan. 2003) to Nov. (Dec.) 2014, inclusive.

	Single	FM	Single	FM	Single	FM	Single	FM
	1	2	3	4	5	6	7	8
%INS_HELD	−0.012	−0.007						
	(−6.46)	(−3.97)						
$\%INS_HELD_{Constrained}$			−0.048	−0.041			−0.076	−0.040
			(−8.05)	(−4.51)			(−3.58)	(−3.86)
$\%INS_HELD_{Unconstrained}$					−0.015	−0.007	0.010	0.002
					(−5.89)	(−3.35)	(1.39)	(0.52)
Intercept	0.476	0.301	0.478	0.284	0.468	0.262	0.452	0.284
	(7.22)	(5.02)	(8.97)	(5.59)	(6.60)	(4.72)	(8.18)	(4.83)
Adj. R^2	68.22%	8.74%	77.08%	10.24%	63.92%	7.77%	78.20%	14.52%
N	20	20	20	20	20	20	20	20

factor model (4) times the corresponding factor excess returns in the same month. The result is a monthly time series of alphas for each of our 20 portfolios. We then perform monthly cross-sectional regressions of month $t+1$ portfolio alphas on month t portfolio-level %INS_HELD. The time-series averages of the monthly cross-sectional regression coefficients, shown in column 2 of Table 6, are consistent with the results of the single regression. The average coefficient on %INS_HELD is negative and highly significant. The average adjusted R^2 value from these monthly cross-sectional regressions is lower than that of the single regression, because the relation between %INS_HELD and alphas is noisier in any given month than in the average month.

If the ultimate driver of the pricing patterns we document is, as we hypothesize, constraints arising from rating-based capital requirements, we expect that the risk-adjusted performance of the portfolios we examine is more closely related to the holdings of constrained insurers than the holdings of unconstrained insurers.[24] To test whether this is the case, we repeat our analysis of the relation between insurer holdings and bond pricing using only holdings by constrained insurers, and then only holdings by unconstrained insurers. We define a bond's $\%INS_HELD_{Constrained}$ to be the percentage of its par value held by constrained insurers, and a bond's $\%INS_HELD_{Unconstrained}$ as the difference $\%INS_HELD - \%INS_HELD_{Constrained}$.

[24]In Section IA-XIII and Tables IA-45 and IA-46 of the Supplementary Material, we show that the underweighting (overweighting) of high-NIG proximity bonds and bonds with low (high) systematic risk exposure is more pronounced among constrained insurers than among unconstrained insurers.

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Following Ellul et al. (2015), we identify constrained insurers as those with an RBC ratio in the bottom quartile of the sample for their type (life or property/casualty). Portfolio-level $\%INS_HELD_{Constrained}$ and $\%INS_HELD_{Unconstrained}$ are then taken to be the MV-weighted averages of the corresponding bond-level values.

Columns 3–8 of Table 6 present the results of the single and FM regressions of portfolio-level alphas on portfolio-level constrained and unconstrained insurer holdings. When included as the only independent variable in the regression specification, $\%INS_HELD_{Constrained}$ (columns 3 and 4) and $\%INS_HELD_{Unconstrained}$ (columns 5 and 6) both have a highly significant negative relation with alpha. When both $\%INS_HELD_{Constrained}$ and $\%INS_HELD_{Unconstrained}$ are simultaneously included in the regression specification (columns 7 and 8), the coefficient on $\%INS_HELD_{Constrained}$ remains negative and highly statistically significant, whereas the coefficient on $\%INS_HELD_{Unconstrained}$ becomes statistically insignificant. The results support the hypothesis that demand from constrained insurers is more strongly related to the pricing effects we document than demand from unconstrained insurers.

B. Insurers' Rating-Based Capital Requirements and Bond Pricing

Having linked the bond-pricing patterns to insurer demand, we next test *H5,* which addresses the concern that some other confounding driver may affect both insurer demand and bond performance. Although rating-based capital requirements for insurers are implemented in 1993, the resultant change in regulated firms' behavior may not have been instantaneous. The regulatory change was debated for several years prior to implementation, and thus some insurers may have altered their investment decisions prior to 1993. Furthermore, penalties for undercapitalized insurers under the new requirements were phased in over several years, and it may have taken insurers time to optimally react to the new regulations. For these reasons, we do not expect to observe an abrupt change in insurer demand and thus in bond pricing in 1993. However, we do expect that the patterns in insurer holdings and bond pricing are, on average, different in the period before than in the period after the implementation of rating-based capital requirements. Furthermore, if these requirements are indeed the driver of the effects we document, the patterns in insurer holdings and bond prices should not exist prior to the regulatory change.

We test H5 by repeating each of the asset-pricing analyses of Section IV using portfolio formation months t (return months $t+1$) from Dec. 1977 (Jan. 1978) to Nov. (Dec.) 1992. We choose the 1978–1992 period, because bond return data are available starting in 1973, making Dec. 1977 the first month for which β^{CBMKT}, β^{TERM}, and β^{DEF} can be calculated using a full 60 months of data.

The results of the portfolio analysis for the 1978–1992 period, shown in Table 7, provide no evidence of pricing patterns prior to the implementation of rating-based capital requirements in 1993. To save space, the table presents only the alphas of the BBB− portfolio, the extreme beta decile portfolios, and the long–short portfolios examined earlier, with complete results provided in Section IA-XIV and Tables IA-47–IA-50 of the Supplementary Material. The results demonstrate that during the 1978–1992 period, BBB− bonds do not generate positive alpha, nor do they generate higher risk-adjusted returns than better-rated bonds. Similarly, the alphas of the beta-sorted extreme decile portfolios are small and, with the exception

TABLE 7

Portfolio Alphas: 1978–1992 vs. 1993–2014

Table 7 presents the alphas of portfolios formed by sorting on noninvestment-grade proximity or systematic risk exposure for the 1978–1992 and 1993–2014 periods. At the end of each month t, we form portfolios as described in Tables 2 and 3. The rows labeled 1978–1992 and 1993–2014 present the intercept coefficient (α) from a regression of excess portfolio returns on TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ. The rows labeled 1978–2014 present the intercept coefficient (α), as well as the coefficient on an indicator variable set to 1 for months Jan. 1993 and after, and 0 otherwise (α^{1993}), from a regression of excess portfolio returns on the indicator variable, TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ, as well as the indicator variable interacted with each of TERM, DEF, STOCKMKT, SMB, HML, MOM, and LIQ. t-statistics, adjusted following Newey and West (1987) using 3 lags and testing the null hypothesis of a zero alpha, are shown in parentheses. Tests for each period cover portfolio formation (return) months t ($t+1$) from December (January) of the (year prior to) the first year in the period to November (December) of the last year in the period.

Period	Value	BBB−	[BBB−]−NAIC 1	[BBB−]−NAIC 2 No BBB−	[BBB−]−IG No BBB−	[BBB−]−BBB	β^{CBMKT} 1	β^{CBMKT} 10	β^{CBMKT} 10−1	β^{TERM} 1	β^{TERM} 10	β^{TERM} 10−1	β^{DEF} 1	β^{DEF} 10	β^{DEF} 10−1
1978–1992	α	0.01	0.01	−0.04	−0.00	−0.05	0.07	0.01	−0.06	0.08	0.01	−0.07	0.02	0.04	0.02
		(0.15)	(0.14)	(−1.06)	(−0.02)	(−1.32)	(2.67)	(0.22)	(−1.01)	(2.79)	(0.20)	(−1.14)	(0.43)	(0.96)	(0.35)
1993–2014	α	0.13	0.14	0.12	0.14	0.09	0.23	−0.12	−0.35	0.21	−0.13	−0.34	0.09	0.01	−0.08
		(3.07)	(2.86)	(2.92)	(3.14)	(2.10)	(9.26)	(−2.85)	(−6.30)	(6.26)	(−2.79)	(−5.77)	(2.24)	(0.36)	(−1.11)
1978–2014	α	0.01	0.01	−0.04	−0.00	−0.05	0.07	0.01	−0.06	0.08	0.01	−0.07	0.02	0.04	0.02
		(0.14)	(0.13)	(−0.88)	(−0.02)	(−1.05)	(2.45)	(0.21)	(−0.93)	(2.05)	(0.17)	(−0.99)	(0.35)	(0.85)	(0.29)
	α^{1993}	0.13	0.14	0.16	0.14	0.14	0.16	−0.13	−0.29	0.14	−0.14	−0.27	0.08	−0.02	−0.10
		(1.93)	(1.82)	(2.70)	(2.08)	(2.29)	(4.23)	(−2.03)	(−3.44)	(2.92)	(−2.04)	(−3.17)	(1.29)	(−0.41)	(−0.99)

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of the β^{CBMKT} and β^{TERM} decile 1 portfolios, statistically insignificant. The results provide no evidence that the β^{CBMKT} $10-1$, β^{TERM} $10-1$, and β^{DEF} $10-1$ portfolios underperform during the 1978–1992 period, since the alphas of each of these portfolios are all statistically indistinguishable from zero.

The corresponding alphas from 1993 to 2014, previously shown in Tables 2 and 3 and repeated here for ease of comparison, suggest a difference in bond-pricing patterns between the 1978–1992 and 1993–2014 periods. To more rigorously test whether the risk-adjusted performance of the portfolios is different before compared to after rating-based capital requirements are implemented, we conduct a factor analysis of the full 1978–2014 time series of portfolio excess returns but allow the alpha and factor exposures to differ after 1993. Specifically, we augment our factor regressions with an indicator variable set to 1 for return months in 1993–2014 and to 0 otherwise, and with this indicator's interaction with the factors. Table 7 presents the alphas from these regressions (complete results provided in Section IA-XIV and Table IA-51 of the Supplementary Material), which indicate that, on average, the performance of the portfolios we examine, except for the β^{DEF}-sorted portfolios, is different during the period in which rating-based capital requirements are in effect than during the period before they are implemented.[25]

C. Alternative Explanations for the Pricing Effects

The results in Sections V.A and V.B provide strong evidence that demand by insurers, induced by rating-based capital requirements, is the driver of the bond-pricing effects we document. Although we cannot completely rule out all other potential drivers, here we present evidence inconsistent with explanations based on intermediary asset pricing, asset–liability maturity matching, and model misspecification, which we view as the most plausible alternatives.

1. Intermediary Asset Pricing

A growing intermediary asset-pricing literature argues that financial intermediaries are the marginal investor in many asset classes and provides empirical evidence that proxies for a stochastic discount factor based on financial intermediaries' marginal value of wealth explain expected asset returns (e.g., Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)). We investigate whether demand by financial intermediaries is responsible for the pricing patterns we document by testing whether exposure to the financial intermediary risk factor of He et al. (2017) or the broker-dealer leverage risk factor of Adrian et al. (2014) explains the outperformance of high-NIG proximity bonds and the underperformance (outperformance) of high-systematic (low-systematic) risk exposure bonds. The results of these tests, presented in Sections IA-XV–IA-XVI and Tables IA-53–IA-60 of the Supplementary Material, provide no evidence that intermediary asset-pricing risk factors are the main driver of the pricing effects we document.

[25] In Section IA-XIV and Table IA-52 of the Supplementary Material, we examine risk-adjusted portfolio returns for more granular subperiods. The results indicate an adjustment period starting in 1993, followed by a relatively stable performance of the long–short portfolios over several subperiods.

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2. Insurer Demand Due to Asset–Liability Matching

Insurers' portfolio allocation decisions are based on several considerations, and matching the maturity of assets with that of liabilities (asset–liability matching hereafter) is one of the most important objectives (see https://naic.soutronglobal.net/Portal/DownloadImageFile.ashx?fieldValueId=7594). The long-term nature of some insurers' liabilities may, therefore, lead them to invest heavily in long-maturity bonds. Since bond maturity and exposure to term factor risk are highly correlated (0.56 in the average month of our sample period and 0.52 in the average month during 1978–1996 according to Gebhardt et al. (2005)), it is plausible that the evidence we present of a negative relation between term beta and risk-adjusted bond returns is driven by asset–liability matching. To determine whether this is the case, we perform several additional analyses.

First, we examine whether insurers indeed tilt their portfolios toward long maturity (MAT) bonds and whether any such tilt can explain our finding that insurers overweight high-β^{TERM} bonds. In Section IA-XVII and Table IA-61 of the Supplementary Material, we show that although insurers do overweight high-MAT bonds during the 2003–2014 period for which holdings data are available, the positive relation between β^{TERM} and insurer holdings persists after controlling for MAT. This suggests that asset–liability matching alone cannot explain the patterns in insurer holdings we document.

Next, we examine the performance of portfolios formed by sorting on MAT. The results, shown in Section IA-XVII and Table IA-62 of the Supplementary Material, are qualitatively similar to those of the β^{TERM} portfolio analyses. During the 1993–2014 (1978–1992) period, there is a strongly significant (weak) negative relation between MAT and α, and the differential performance between the 2 periods is significant.

Finally, to test whether the negative relation between term factor risk exposure and risk-adjusted bond returns can be explained by maturity, we examine the performance of portfolios constructed by first sorting bonds into MAT deciles and then, within each MAT decile, into β^{TERM} deciles. The results of these analyses are presented in Section IA-XVII and Table IA-63 of the Supplementary Material. We find that the β^{TERM} $10-1$ portfolios in each MAT decile, including the average MAT decile, have significantly positive postformation exposure to TERM, indicating that even after controlling for maturity, we are able to generate portfolios with dispersion in exposure to term factor risk. The alphas of the β^{TERM} $10-1$ portfolios are negative in all MAT deciles, and significant in most, including the average MAT decile. These results demonstrate that rating-based capital requirements, and not simply asset–liability matching, drive the negative relation between term factor risk exposure and risk-adjusted bond returns we document.

3. Model Misspecification

Since a misspecified factor model could produce significant alphas even when assets are correctly priced, we next consider the possibility that a poorly specified model could be the driver of the pricing effects we document. If model misspecification were responsible for our findings, we would expect the model to produce

significant alphas in both the 1978–1992 and 1993–2014 periods.[26] The absence of significant alphas prior to 1993 suggests that model misspecification does not drive our results. To further investigate whether our model correctly prices the portfolios we analyze during the 1978–1992 period, when we do not expect the pricing patterns to exist, we conduct Gibbons, Ross, and Shanken (GRS) (1989) tests on these portfolios. If our factor model is poorly specified, the GRS tests should reject the null hypothesis that the model correctly prices all of the portfolios. In Section IA-XVIII and Table IA-64 of the Supplementary Material, we show that the GRS tests fail to reject this null hypothesis. Finally, as discussed in Sections IA-IV–IA-VII and Tables IA-8–IA-31 of the Supplementary Material, our results are robust when using several different factor models and alternative definitions for the CBMKT, TERM, and DEF factors, and when we add an aggregate bond liquidity risk factor or the Bai et al. (2019) factors to our model.

VI. Conclusion

In this article, we show that capital regulations, through their impact on investment demand, affect equilibrium market prices. Specifically, we document 2 patterns in corporate bond prices and attribute them to insurer demand induced by rating-based capital requirements. First, we demonstrate that IG bonds with high NIG proximity generate positive risk-adjusted returns, and bonds with high (low) systematic risk exposure generate negative (positive) risk-adjusted returns. We then document that insurers do indeed invest proportionally less in high-NIG proximity bonds and proportionally more (less) in bonds with high (low) systematic risk exposure. Importantly, these patterns in insurer holdings explain most of the patterns in bond pricing. Finally, we show that the patterns do not exist prior to the implementation of rating-based capital requirements for insurers in 1993.

Our article contributes to several important policy debates on the unintended consequences of capital regulations. First, since market prices are known to influence industrial firms' real investment decisions, we provide a clear link between capital regulations and real economic outcomes. Because persistent alphas have greater implications for corporate investment than transient alphas, the persistence of the pricing patterns we document suggests that the real economic consequences of capital regulations for *unregulated* firms can be considerable.

A second implication of our results is that by creating an incentive among insurers to invest in high-systematic risk exposure bonds, rating-based capital requirements may contribute to a buildup of systemic risk in the economy. Regulators have expressed a concern that insurers' interconnectedness through their portfolio holdings may pose a threat to financial stability. Consistent with this concern, insurers' preference for the most systematically risky bonds makes their portfolio returns both highly correlated and highly sensitive to economic downturns. Furthermore, insurers' tendency to overinvest in high systematic risk borrowers may also contribute to the procyclicality of real investment. Enhanced

[26]Exceptions to this statement could arise if bond market beta and term beta were cross-sectionally uncorrelated with beta on the omitted factor before 1993 but correlated with this beta after 1993, or if an omitted factor did not carry a risk premium prior to 1993 and did carry a risk premium post 1993.

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awareness of these effects of capital regulations on the real economy and systemic risk is particularly valuable to prudential regulators whose objective is to balance the benefits of a safe and sound insurance industry against the costs of capital regulations' unintended consequences.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109021000132.

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