The Bond Pricing Implications of Rating-Based Capital Requirements*

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Abstract

This paper 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 (IG) bonds with a rating close to non-investment-grade, these bonds are underpriced. Consistent with insurers' high (low) demand for IG bonds with high (low) systematic risk exposure, these bonds are overpriced (underpriced). 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.

Keywords: Risk-based capital, regulatory arbitrage, insurance companies, corporate bonds, credit ratings, systematic risk, asset pricing
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1 Introduction

This paper 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 (2018)). Recent theoretical work links investor demand for assets with certain characteristics to asset prices (e.g., He and Krishnamurthy (2013) and Koijen and Yogo (2016)). In particular, the model of Harris, Opp, and Opp (2017) 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 paper 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 two 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 the marginal 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 (Ellul, Jotikasthira, and Lundblad (2011) and Becker and Ivashina (2015)). These incentives lead to two specific hypotheses about patterns in bond prices that are attributable to insurers' capital regulations.

The first hypothesis derives from the literature's empirical finding that high capital charges for non-investment-grade (NIG) bonds encourage insurers to quickly sell bonds downgraded from IG to NIG, which results in short-lived underpricing of these bonds (Ellul et al. (2011) and Ambrose, Cai, and Helwege (2008)). 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 such bonds. Thus, our first hypothesis is that as a result of low demand, bonds with high NIG proximity (IG bonds with a rating close to NIG) are underpriced.[1]

Our second bond pricing hypothesis is based on the theoretical argument that risk-based capital requirements that do not fully reflect systematic risk, when coupled with guaranty funds, lead insurers to tilt their portfolios towards systematically risky bonds (Pennacchi (2006)). Guaranty funds, which cover the claims of insolvent insurers' policyholders, create an incentive for insurers to take on more risk than they otherwise would (Cummins (1988) and Lee, Mayers, and Smith (1997)). Risk-based capital requirements are intended to thwart this incentive by tying required capital to portfolio risk. However, required capital charges for corporate bonds are based on broad credit

[1] Throughout this paper, the terms "underpriced" and "overpriced" should be understood as relative to a frictionless benchmark equilibrium and the mispricing we document should be viewed as reflecting a new equilibrium resulting from regulatory capital constraints. Black (1972), Frazzini and Pedersen (2014), and Harris et al. (2017) develop equilibrium models in which leverage constraints cause equilibrium prices to diverge from their frictionless benchmark.

rating-based categories and within each category there are bonds with different levels of systematic risk exposure. Therefore, among bonds in the same capital charge category, insurers have incentive to boost expected portfolio return by tilting holdings toward (away from) high-systematic (low-systematic) risk exposure bonds, thereby creating high (low) demand for such bonds. Thus, our second hypothesis is that as a result of high (low) demand, conditional on required capital charge, bonds with high (low) systematic risk exposure are overpriced (underpriced).

We test our two bond pricing hypotheses by examining a comprehensive sample of IG corporate bond returns from the 1993-2014 period, when rating-based capital requirements for insurers are in place.[2] Specifically, we analyze the risk-adjusted returns of bond portfolios designed to have variation in NIG proximity or systematic risk exposure. Bonds that are overpriced (underpriced) should generate negative (positive) future risk-adjusted returns. In support of our first hypothesis, 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 hypothesis, we find that conditional on capital charge, bonds with high (low) systematic risk exposure generate negative (positive) risk-adjusted returns. The result holds for exposure to aggregate IG corporate bond market risk (bond market risk hereafter) and systematic term risk, but not for systematic default risk. These pricing effects last for at least twelve 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) and Ellul, Jotikasthira, Lundblad, and Wang (2015)).

We next test the hypothesis that 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 towards (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 both bond market risk and systematic term risk. We then investigate the extent to which insurer investment demand explains the observed pricing patterns. Our tests indicate that the mispricing associated with NIG proximity and systematic risk exposure is strongly related to insurer holdings. Taken together, these results support our hypothesis that the outperformance of bonds with high NIG proximity and underperformance (outperformance) of bonds with high (low) systematic risk exposure are driven by insurer investment demand.

Finally, we examine the hypothesis that rating-based capital requirements are the driver of the

[2] We focus on the IG segment of the corporate bond market for two 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)). 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 1). 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.

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 than in the period after the implementation of rating-based capital requirements. Consistent with our hypothesis, 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 capital requirements are in place.

Our results allow us to rule out demand by other corporate bond market investors and factor model misspecification as alternative explanations for the pricing patterns we document. While banks are subject to ratings-based capital charges that are similar in structure to those of insurers, banks' own only a small portion of the corporate bond market, and only a small portion of banks' portfolios are invested in corporate bonds. Thus, demand from banks is unlikely to move prices and banks have little incentive to adjust their corporate bond investments to minimize required capital. Furthermore, the pricing patterns we document were present prior to 2007, when ratings-based capital requirements for banks that distinguish among corporate bonds of different ratings went into effect. Many pension funds, mutual funds, and exchange traded funds have guidelines that limit their investment in NIG bonds. However, these investors face little pressure to quickly sell bonds downgraded from IG to NIG (Cantor, ap Gwilym, and Thomas (2007)), which may weaken their aversion to high-NIG proximity bonds. Additionally, managers of these funds are usually evaluated on a risk-adjusted basis, giving them little incentive to tilt their portfolios towards high-systematic risk bonds. Furthermore, because the pricing patterns evident during the 1993–2014 period are not present during the 1978–1992 period, for demand by another set of investors to be consistent with our results, that set of investors would need to have had different investment incentives in the early and latter part of our sample period. To our knowledge, there is no reason to think that this is the case for pension funds, mutual funds, or exchange traded funds. Finally, we rule out model misspecification as a potential explanation for the pricing effects we document by showing that our findings are robust to a large number of alternative factor models and that the portfolios we examine are correctly priced during the 1978-1992 period.

In sum, our results show that insurer investment demand induced by rating-based capital requirements has a substantial impact on the equilibrium prices of corporate bonds. This finding adds to recent work on the implications of insurers' investment decisions for the U.S. corporate bond market. Ellul et al. (2011) examine 1,179 bonds downgraded from IG to NIG between 2001 and 2005 and demonstrate that fire sales by insurers around these downgrades cause short-lived deviations of market prices from fundamental values. In contrast, our paper shows 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 equilibrium prices to diverge from their frictionless benchmark. Becker and Ivashina (2015) analyze 600 IG bonds issued between 2004 and 2007, and find that large primary market purchases by insurers are related to poor bond performance immediately after issuance. We expand on this finding by showing that insurers' demand affects prices long after issuance and that this effect is driven by insurers' demand for high-systematic risk exposure bonds. Another important distinction between these previous 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. This is important because persistent distortions in a large cross-section of bond prices has ramifications for the cost of capital of many firms, which may cause deviations from optimal aggregate investment (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), Warusawitharana and Whited (2016), and Van Binsbergen and Opp (2017)). Finally, we extend prior work by providing evidence linking the pricing effects we document to capital regulations: the effects are non-existent prior to the implementation of rating-based capital requirements.

Our work also contributes to three broader strands of the literature. First, we add to a growing number of studies on the unintended consequences of regulatory reliance on credit ratings. Pennacchi (2006) and Iannotta et al. (2018) develop theoretical models to demonstrate that rating-based capital requirements create incentives for regulated firms to increase their systematic risk exposure, thus making these firms more likely to suffer losses during an economic downturn and undermining the goal of prudential regulations. Acharya and Richardson (2009), Calomiris and Mason (2010), White (2010), Stanton and Wallace (2018), Opp, Opp, and Harris (2013), and Cornaggia, Cornaggia, and Hund (2017) provide empirical evidence that ratings-based capital requirements lead to various forms of regulatory arbitrage by financial firms, which may leave these firms undercapitalized and pose a threat to the stability of the financial sector. The use of ratings in financial regulations also affects the allocation of credit among industrial firms (Becker and Ivashina (2015)) and these firms' cost of capital (Kisgen and Strahan (2010)). We document another unintended consequence of regulatory reliance on ratings: a distortion in the equilibrium prices of corporate bonds in the secondary market. We then establish regulated institutions' investment demand as the channel through which this distortion takes place.

Second, our paper provides empirical support to the theoretical literature on the asset pricing implications of institutional investor demand (e.g., He and Krishnamurthy (2013) and Koijen and Yogo (2016)). We focus on insurers' demand driven by rating-based capital requirements, and document that it affects equilibrium corporate bond prices. This is consistent with the theoretical prediction of Harris et al. (2017) that capital requirements that measure the risk of assets imperfectly cause distortions in the cross-section of asset prices. While previous empirical research has documented persistent distortions in the pricing of stocks (Gompers and Metrick (2001)) and loans (Ivashina and Sun (2011)) due to institutional demand, to our knowledge we are the first to link such an effect to capital regulations.

Finally, our paper 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), Crawford, Perotti, Price, and Skousen (2015), Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017), and Choi and Kim (2018) show that anomalies previously documented in the equity market are present in the corporate bond market as well. Our study adds to this literature by demonstrating that rating-based capital requirements, which are unique to credit markets, are important for the cross-section of bond returns.

The rest of the paper is organized as follows. Section 2 discusses insurers' guaranty funds, capital requirements, and the effect of these on insurers' investment demand. It then specifies our testable hypotheses. Section 3 describes our data sources and sample construction. Section 4 presents evidence of the hypothesized patterns in bond pricing. Section 5 establishes rating-based capital requirements, through their impact on insurer investment demand, as the driver of these pricing patterns. Section 6 concludes.

2 Institutional Background and Hypotheses

In this section we describe the investment incentives created by insurers' risk-based capital requirements. Based on this discussion, we develop our hypotheses.

2.1 Insurer Capital Requirements and Investment Incentives

The focus of our paper is insurers' risk-based capital requirements. However, since the need for risk-based capital requirements arises from the existence of insurer guaranty funds, we begin with a discussion of these funds and their effect on insurers' investment incentives.

Insurer guaranty funds, established mostly during the 1970s and still in existence today, guarantee the benefits of an insolvent insurer's policyholders.[3] When an insurer becomes insolvent and is unable to satisfy policyholders' claims, the claims are covered through assessments against surviving insurers operating in the same state (Munch and Smallwood (1980)).[4] Guaranty funds structured in this manner are meant to encourage insurers to monitor their competitors and report any excessive risk-taking to state regulators. However, in many states assessments can be recovered through rate increases or tax offsets (Lee et al. (1997)), thus weakening the intended monitoring incentive. In sum, guaranty funds enable insurers to take on risk without bearing its full cost (Cummins (1988)), thereby inducing insurers to take on more risk than they otherwise would (Lee et al. (1997)).

Capital requirements for insurers were implemented in part to reign in the risk-taking incentives created by state guaranty funds. Early efforts to ensure that insurers had sufficient equity to cover

[3] Guaranty funds were established by states at different times between 1969 and 1981 (Lee et al. (1997)). All but two states, Alabama and Oklahoma, had guaranty funds in place by 1978. Oklahoma established its guaranty fund in 1980 and Alabama did so in 1981.

[4] In all states except New York, guaranty funds are funded post-insolvency and assessments are a flat percentage of the surviving insurers' premiums in the state (Duncan (1984)). The New York guaranty fund is pre-funded through quarterly assessments until a certain prescribed level is reached.

policyholders' losses took on two forms. First, acquiring a state insurance license required an initial fixed dollar amount of equity capital that varied with insurer ownership form and line of business (Munch and Smallwood (1979) and Grace et al. (1998)). Second, to make certain that capital grew as an insurer grew, state regulators encouraged, though did not require, insurers to hold more capital as their premiums written increased (Munch and Smallwood (1979)). Importantly, these early capital requirements did not constrain in a meaningful way insurers' leverage or the risk of insurers' investments, and thus did little to curb the incentive for insurers to take on risk.

This changed in 1993 when insurer regulators introduced risk-based capital requirements.[5] Specifically, regulators adopted the ratio of actual capital (i.e., total adjusted capital) to required capital (i.e., authorized control level risk-based capital), commonly referred to as the risk-based capital (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. Figure 2 shows the composition of insurers' portfolios through time. The figure indicates that insurers invest primarily in fixed-income securities, and that of these, corporate bonds are the most represented asset class. As a result, the credit quality of an insurer's corporate bond holdings has a first order impact on its RBC ratio.

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.[6] Designations take integer values from 1 to 6 with higher numbers implying worse credit quality. The NAIC designation determines the amount of capital an insurer must hold to cover expected credit losses on a security, and as Table 1 shows, securities with higher NAIC designations have higher required capital charges.

For corporate bonds, NAIC designations are exclusively based on credit ratings issued by approved credit rating providers (CRPs).[7] Table 1 summarizes the one-to-one mapping from ratings to NAIC designations and illustrates two important points. First, required capital charges increase as credit rating worsens, with the best-rated NIG bonds requiring significantly more capital than the worst-rated IG bonds. Second, bond risk not captured by ratings is irrelevant for regulatory capital purposes. We argue that these features of insurers' rating-based capital requirements create strong incentives to avoid holding IG bonds with a rating close to NIG and prefer holding IG bonds with high systematic risk exposure.

Empirical studies confirm that rating-based capital requirements play an important role in in-

[5]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.

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

[7]The current list of approved CRPs includes nine companies (Moody's, Standard & Poor's, 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, Standard & Poor's, Fitch, DBRS, and A.M. Best. While a long history of CRP market share is not available, the Security and Exchange Commission's 2016 Annual Report on Nationally Recognized Statistical Rating Organizations indicates that in 2015 89% of outstanding corporate bond ratings were provided by Moody's, Standard & Poor's, and Fitch (https://www.sec.gov/ocr/reportspubs/annual-reports/2016-annual-report-on-nrsros.pdf). In our analysis, we focus on credit ratings by these three CRPs.

surers' 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. 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. This creates a strong incentive for insurers to avoid investing in IG bonds with high NIG proximity.

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. Without the constraint imposed by capital requirements, insurers can increase systematic risk either by tilting their portfolios towards 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 their ability to borrow or to invest in high-systematic risk securities. 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 tilt their portfolios towards (away from) bonds with higher (lower) systematic risk, thereby increasing the systematic risk of their portfolios without increasing required capital. Increasing leverage to take on risk, on the other hand, would increase insurers' required capital. The incentive for increased systematic-risk taking when capital requirements do not fully account for the systematic risk of investments is formally modeled by Pennacchi (2006) and finds empirical support in Becker and Ivashina (2015) and Iannotta et al. (2018). Becker and Ivashina (2015) provide evidence from the primary market that insurers "attempt to increase the yield in their bond portfolio by taking on extra priced risk, while leaving capital requirements unaffected." Similarly, Iannotta et al. (2018) find that capital-constrained U.S. commercial banks tend to invest in syndicated loans with higher systematic risk exposure. In sum, rating-based capital requirements effectively function as a leverage constraint on insurers' portfolios, and this leverage constraint creates a strong incentive for insurers to tilt their portfolios towards bonds with high systematic risk exposure.

2.2 Hypotheses

In this paper we argue that insurers' low demand for corporate bonds with high NIG proximity and high (low) demand for corporate bonds with high (low) systematic risk exposure, both induced by rating-based capital requirements, impact equilibrium IG corporate bond prices. Insurers are the largest investors in corporate bonds, holding about a third of the total market value outstanding (Figure 1). Thus, insurers are likely to be the marginal investor in the IG segment of the corporate bond market. If the supply of corporate bonds is not perfectly elastic, the effect of insurers' demand on bonds' demand curves will impact equilibrium bond prices, causing highly-demanded (lowly-demanded) bonds to be relatively overpriced (underpriced). This argument is similar to that made by empirical studies of the equity and loan markets documenting that demand by important market participants has a persistent impact on prices in these markets (Shleifer (1986), Gompers and Metrick (2001), and Ivashina and Sun (2011)).

Our reasoning leads to four hypotheses that we test in the remainder of the paper. The first two hypotheses, *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.

> ***H1:*** *IG bonds with high NIG proximity are, on average, underpriced.*
>
> ***H2:*** *Conditional on capital charge, IG bonds with high (low) systematic risk exposure are, on average, overpriced (underpriced).*

Hypothesis *H1* is driven by insurers' rating-based capital requirements, which generate fire sales when IG bonds are downgraded to NIG, and thus discourage insurers from investing in bonds immediately above the the NIG threshold. Hypothesis *H2* is driven by the interaction between guaranty funds, which create an incentive for insurers to increase risk, and the structure of rating-based capital charges, which constrains leverage but does not constrain risk-taking that is not captured by ratings. Frazzini and Pedersen (2014) demonstrate theoretically that leverage constraints on important market participants result in the overpricing (underpricing) of securities with high (low) systematic risk exposure.

Securities that are underpriced are expected to generate high risk-adjusted future returns. Therefore, we test *H1* by examining whether a portfolio of high-NIG proximity bonds generates positive risk-adjusted returns. Similarly, we test *H2* by examining whether a portfolio of high-systematic (low-systematic) risk exposure bonds produce negative (positive) risk-adjusted returns. For both *H1* and *H*2, we investigate whether the pricing effects reflect long-term equilibrium prices by examining whether the effects are persistent. These tests cover the 1993-2014 period, when rating-based capital requirements are in effect.

Our next hypothesis, *H3,* identifies insurer demand as the driver of the pricing effects hypothesized in *H1* and *H2.*

> ***H3:*** *Insurers' low demand for IG bonds with high NIG proximity and high (low) demand for bonds with high (low) systematic risk exposure drive the pricing patterns predicted by hypotheses H1 and H2.*

We test *H3* in two steps. First, we investigate whether insurers' holdings of corporate bonds are indeed tilted away from high-NIG proximity bonds and towards high-systematic risk bonds. Second, we examine whether the tilts in insurer holdings explain the hypothesized patterns in bond performance.

Finally, our hypothesis *H4* ties insurer demand, and ultimately bond performance, to rating-based capital requirements.

H4: *Rating-based capital requirements are the driver of insurers' low demand for IG bonds with high NIG proximity and high (low) demand for bonds with high (low) systematic risk exposure, and therefore ultimately of the pricing patterns predicted by hypotheses H1 and H2.*

We test *H4* by examining whether the pricing effects hypothesized in *H1* and *H2* exist in the absence of rating-based capital requirements by repeating our tests of these hypotheses using the 1978-1992 period, which is prior to the requirements' implementation.

3 Data and Sample

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

3.1 Bond Returns and Characteristics

Bond returns are constructed from four different sources: (1) Lehman Brothers' Fixed Income Database (Lehman), (2) Thomson Reuter's DataStream (DataStream), (3) Mergent's National Association of Insurance Commissioners Database (MNAIC), and (4) FINRA's TRACE and TRACE Enhanced (TRACE/TRACE Enhanced). Other recent studies (e.g., Jostova et al. (2013) and Chordia et al. (2017)) similarly combine data from these sources to construct a long-time series and broad cross-section of monthly corporate bond returns.

Lehman provides monthly bond returns for the period from January 1973 through March 1998.[8] Most returns reflect dealer quotes, but some are based on "matrix" prices derived from quotes of bonds with similar characteristics. Like Gebhardt et al. (2005) and Jostova et al. (2013), we use returns based on both quote and matrix prices.[9]

From DataStream, we collect end-of-month bond prices for the period from January 1990 through December 2014.[10] Prices in DataStream are based on dealer quotes or transaction prices.

The MNAIC database contains information on bonds acquired or disposed of by insurers from January 1994 through December 2014. We keep only records pertaining to trades, and remove records related to non-trading activity (e.g., maturity, repayment, and calls).

Finally, we collect data on all transactions in publicly traded TRACE-eligible securities between July 2002 and March 2014 from FINRA's TRACE Enhanced database. The data end in March 2014 because FINRA distributes TRACE Enhanced data with an 18-month lag. We therefore augment TRACE Enhanced data with TRACE data from April 2014 through December 2014. TRACE data are available in real time and during this period include all trades that will eventually be

[8]Data are largely unavailable for August 1978 and December 1984.

[9]In Section I and Tables A1-A5 of the Internet Appendix, we demonstrate that our results hold when we exclude returns based on matrix prices from our sample.

[10]We calculate returns from price data instead of from DataStream's cumulative total return indices because we detect errors in these indices. The errors include negative index values (28 securities affected), decreasing index values but increasing prices (more than 4,000 securities affected), and missing index values when price and accrued interest data are available (more than 3,000 securities affected).

distributed through TRACE Enhanced.[11] Taken together, the TRACE/TRACE Enhanced data provide a comprehensive database of transactions in TRACE-eligible securities from July 2002 through December 2014. We filter out trade cancellations and corrections using the approach in Dick-Nielsen (2009) and Dick-Nielsen (2014), and also remove trades where the reported price cannot be correctly interpreted as the transaction price.[12]

The MNAIC and TRACE/TRACE Enhanced databases provide intraday transaction data. For these databases, we follow Jostova et al. (2013) and Chordia et al. (2017) and construct daily prices as the trade size-weighted average of intraday prices.[13] The month-end price is then taken to be the last available daily price from the last five trading days of the month. We combine MNAIC and TRACE/TRACE Enhanced month-end prices into one data set, giving precedence to the latter when prices are available from both sources.[14]

We then use month-end prices from DataStream or from the combined TRACE/TRACE Enhanced/MNAIC data to calculate monthly returns separately for each dataset.[15] The return of bond i in month t, $r_{i,t}$, is calculated as:

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

where $P_{i,t}$ is the bond's clean price at the end of month t, $AI_{i,t}$ 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. Coupon information and data needed to calculate accrued interest come from Mergent's Fixed Income Securities Database (FISD) and Thomson Reuter's DataScope (DataScope).[16] We do not calculate returns for bonds with variable-rate coupons or bonds with non-standard coupon features (step-up, increasing-rate, pay-in-kind, and split-coupon) because we have no information on how these bonds' coupons change over time.

We combine monthly returns from the three different datasets, giving precedence to trade-based returns. When returns for the same bond-month observation are available from multiple

[11] We use TRACE Enhanced for the early part of the sample for two reasons. First, prior to 2005 TRACE is incomplete due to its gradual phase-in and therefore contains only a subset of the trades in TRACE Enhanced. Second, for the entire period, TRACE reports the size of all IG bond trades larger than \$5 million as "\$5MM+" whereas TRACE Enhanced reports the actual trade size.

[12] Specifically, we remove agency customer transactions without commission, when-issued trades, locked-in trades, trades with special sales conditions, trades with more than three days to settlement, and commission trades.

[13] This approach is motivated by Bessembinder, Kahle, Maxwell, and Xu (2009), who find that using trade size-weighted intraday prices minimizes the impact of the bid-ask bounce and results in more informative prices than using the last traded price of the day. We do not exclude trades of \$100,000 or less because, as discussed in O'Hara, Wang, and Zhou (2018), insurers frequently execute such trades.

[14] Combining TRACE/TRACE Enhanced and MNAIC month-end prices prior to calculating monthly returns allows us to retain observations where a price is available in one database in one month and the other database in the next month, but not available in any one database in both months.

[15] Before calculating monthly returns, we remove from all databases observations with negative prices as well as observations with issuance or trade dates after the maturity date, since these observations are obvious data errors.

[16] Computing accrued interest requires the bond's coupon amount, coupon frequency, and day count convention. Following Jostova et al. (2013), we assume a semi-annual coupon frequency if the coupon frequency is missing, and 30/360 day count convention if the day count convention is missing. If information on the bond's coupon amount is missing, we do not calculate a return.

sources, we take the first available return in the following sequence: combined TRACE/TRACE Enhanced/MNAIC, Lehman, and DataStream. To ensure data quality we follow Jostova et al. (2013) and remove the bottom and top 0.5 percent 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 one-month U.S. Treasury bill.[17]

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 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 two are available and the second lowest rating when three are available (Becker and Ivashina (2015)). These regulatory ratings are then converted to NAIC designations using the mapping in Table 1. Data on bond par value outstanding are taken from FISD, 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.[18]

We retain return observations for corporate bonds traded in the U.S. with at least one year to maturity. We exclude observations for bonds with less than one year to maturity following Warga (1991) and Eom, Helwege, and Huang (2004), because bonds become relatively illiquid when close to maturity. 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. However, 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.

3.2 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. Fama and French (1993) and Gebhardt, Hvidkjær, and Swaminathan (2005) suggest that two 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. 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 one-month U.S. Treasury bill. 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.

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

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

If, as suggested by Fama and French (1993) and Gebhardt, Hvidkjær, and Swaminathan (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.[19]

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), Bai, Bali, and Wen (2018), and Choi and Kim (2018)), which implicitly assumes that the term factor exposure of both the long and short portfolios is the same.[20] Indeed, our analysis suggests that the exposure of the aggregate bond market to term risk is only about 0.30 (see discussion in next paragraph). Thus, if we were to take DEF to be the difference between $CBMKT$ and $TERM$, while $TERM$ 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.[21] Nonetheless, in Section IV and Tables A14-A24 of the Internet Appendix, we perform several robustness tests to ensure that our results do not depend on our factor definitions.

Table 2 presents summary statistics for the monthly factor excess returns for 1993-2014, the period examined in the tests of our two bond pricing hypotheses, *H1* and *H2*. Panel A shows that $CBMKT$ generates an average (median) excess return of 0.35% (0.40%) per month, with a standard deviation of 1.28%. $TERM$ produces an average monthly excess return of 0.47% with a standard deviation of 2.84%. Summary statistics for DEF are generated from a regression of $CBMKT$ on

[19]Lin, Wang, and Wu (2011), Dick-Nielsen, Feldhütter, and Lando (2012), Acharya, Amihud, and Bharath (2013), and Bongaerts, de Jong, and Driessen (2017) suggest that a liquidity factor is an important driver of corporate bond returns. Our main bond pricing tests adjust for exposure to aggregate stock liquidity. In Section II and Tables A6-A9 of the Internet Appendix, we demonstrate that the pricing patterns we document persist after accounting for aggregate bond liquidity. We also investigate whether there is an intermediary asset pricing-based explanation for our findings by including Adrian, Etula, and Muir (2014)'s broker-dealer leverage risk factor in our factor model. The results of tests in Section III and Tables A10-A13 of the Internet Appendix rule out this explanation.

[20]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 $TERM$.

[21]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 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.

$TERM$ using data from 1993-2014. The intercept coefficient from the regression indicates that DEF generates a premium of 0.21% per month, which is notably smaller than the premium generated by $TERM$. The regression's slope (unreported in the table) coefficient is 0.30, suggesting that the exposure of the aggregate IG corporate bond market to term factor risk is substantially less than one. The standard deviation of the regression residuals, which reflects default factor variation, is 0.95% per month. Panel B shows that during 1993-2014, the correlation between $CBMKT$ and $TERM$ is 0.67, while that between $CBMKT$ and DEF is 0.74. The correlation between DEF and $TERM$ is zero by construction.

3.3 Proximity to NIG

NIG proximity is intended to capture the possibility that a bond is downgraded to NIG. Figure 3 shows that over horizons of one to 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 eight times more often than BBB bonds. We therefore take bonds with a BBB− regulatory rating to be bonds with high NIG proximity.[22]

3.4 Systematic Risk Exposure

We measure bonds' systematic risk exposure (beta) to the three bond factors described in Section 3.2: 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 $CBMKT$. The regression specification is:

$$R_{i,t} = \beta_i^0 + \beta_i^{CBMKT} CBMKT_t + \epsilon_{i,t}. \tag{2}$$

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:[23]

$$R_{i,t} = \beta_i^0 + \beta_i^{TERM} TERM_t + \beta_i^{DEF} DEF_t + \nu_{i,t}. \tag{3}$$

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. 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

[22] 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−.

[23] 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).

of 24 monthly bond return observations during the 60-month estimation window. Betas for bond-month observations not satisfying this criterion are considered missing.

3.5 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 one 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. Table 3 Panel A 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 the percentage of BBB− bonds reported separately. 62% 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 3. 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 high correlation between $CBMKT$ and $TERM$ (Table 2). 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). 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}.

4 Bond Pricing

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

4.1 NIG Proximity and Bond Pricing

We first test our hypothesis *H1* that IG bonds with high NIG proximity are underpriced. We do so by investigating whether a portfolio of bonds rated BBB−, which as we discuss in Section 3.3 have high NIG proximity, generate positive risk-adjusted returns. Additionally, to ensure that any mispricing 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 five 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 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 four 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:

$$R_{p,t+1} = \alpha_p + \boldsymbol{\beta^F_{Post,p} F_{t+1}} + \varepsilon_{p,t+1} \tag{4}$$

where $R_{p,t+1}$ is portfolio p's post-formation excess return, $\boldsymbol{F_{t+1}}$ is a vector of month $t+1$ factor-mimicking portfolio excess returns, and $\boldsymbol{\beta^F_{Post,p}}$ is a vector of coefficients measuring the post-formation exposures of the portfolio to the factors in $\boldsymbol{F_{t+1}}$. The estimated intercept α_p measures the risk-adjusted return (alpha) generated by the portfolio, where the risk-adjustment reflects expected returns under a frictionless benchmark. A positive (negative) alpha indicates that the portfolio outperforms (underperforms) the benchmark, meaning that the bonds in it are, on average, under-priced (overpriced). If the bonds in the portfolio are correctly priced, i.e. the portfolio's return is commensurate with its risk, then the alpha should be zero, indicating that the market's pricing of the portfolio is consistent with the frictionless benchmark.

While 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 $\boldsymbol{F_{t+1}}$. 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).[24] As long as the factors included in our model span the true set of factors important for pricing our sample bonds, the estimated coefficient α_p is an unbiased estimate of the portfolio's risk-adjusted performance. Inclusion of unimportant or redundant factors does not bias the estimate of α_p, but does increase its standard error. Our inclusion of a large set of stock return factors in the factor model reflects our choice to be conservative in our assessment of risk-adjusted performance. In Sections II-V and Tables A6-A29 of the Internet Appendix, we demonstrate that our results from this and subsequent sections are robust when using alternative factor models.

[24]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.

Since $TERM$ and DEF are pure term and default 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. This orthogonalization does not affect the estimate of α_p or its statistical significance, but it ensures that $\beta^{TERM}_{Post,p}$ and $\beta^{DEF}_{Post,p}$ accurately measure the portfolio's post-formation exposures to term and default factor risk, respectively.[25]

Our hypothesis *H1* predicts that the BBB− portfolio, as well as portfolios that are long BBB− bonds and short other IG bonds, should generate a positive alpha. The results of the portfolio analyses, shown in Table 4, strongly support this hypothesis. 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 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).[26] Consistent with ratings measuring idiosyncratic but not systematic risk (Iannotta et al. (2018)), the long-short portfolios have economically small and in most cases statistically insignificant post-formation risk factor exposure.[27]

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. Our first two tests identify subsets of BBB− bonds that have higher NIG proximity than others and examine whether their outperformance is stronger. First, since for bonds rated by all three CRPs the middle of the three ratings is the one used for regulatory capital purposes, some bonds we classify as BBB− have an even worse rating from one of the CRPs. In Section VII.A and Table A34 of the Internet Appendix, we take these bonds to have even higher NIG proximity than other BBB− bonds and show that, consistent with our hypothesis, while outperformance is strong in both groups of BBB− bonds, it is stronger among BBB− bonds that are rated NIG by one CRP. Second, Lando and Skødeberg (2002) document momentum in bond

[25] Another ramification of orthogonalizing $STOCKMKT$, SMB, HML, MOM, and LIQ to $TERM$ and DEF is that the estimated coefficients $\beta^{TERM}_{Post,p}$ and $\beta^{DEF}_{Post,p}$, and their inferential statistics, are exactly the same as those that would have resulted from estimating a two-factor model with $TERM$ and DEF as the factors, which is how we estimate the ex-ante values of $\beta^{TERM}$and β^{DEF} (see equation (3)).

[26] 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 driven by the events of this period, in Section VI and Tables A30-A33 of the Internet Appendix we remove the financial crisis period from our sample and repeat our main bond pricing tests. The results are qualitatively unchanged.

[27] Nanda, Wu, and Zhou (2017) argue that rating-based capital requirements result in fire sale risk being a priced factor. Interpreted in this light, our long-short portfolio returns may serve as empirical proxies for a fire sale risk factor and the alpha generated by these portfolios as compensation for exposure to this factor.

ratings, suggesting that BBB− bonds recently downgraded from a better rating have higher NIG proximity than other BBB− bonds. In Section VII.B and Table A35 of the Internet Appendix we isolate recently downgraded BBB− bonds and show that, as expected, they have higher risk-adjusted returns than other BBB− bonds. Again, both groups of BBB− bonds outperform various subsets of other IG bonds. Since bonds rated BBB have the second highest NIG proximity, our third test examines the performance of long-short portfolios that are long bonds rated BBB and short better-rated bonds. Consistent with bonds rated BBB being closer to an NIG rating than better-rated bonds, albeit not nearly as close as BBB− bonds, Section VII.C and Table A36 of the Internet Appendix show that these long-short portfolios generate positive but economically small and statistically weak risk-adjusted returns. Finally, since bonds rated A− are the worst-rated bonds with NAIC designation of 1, and any downgrade of these bonds would result in a slightly higher required capital charge, it is possible that insurers are also averse to owning bonds rated A−, and that this aversion affects prices. Tests of this hypothesis, shown in Section VII.D and Table A37 of the Internet Appendix, provide no evidence that bonds rated A− have differential performance. This is consistent with the evidence in Becker and Ivashina (2015) that the threshold between NAIC designation 1 and 2 does not affect insurers' purchases of newly issued bonds, which suggests that insurers do not fire sell bonds downgraded across the A− to BBB+ threshold.

4.2 Systematic Risk Exposure and Bond Pricing

We turn now to testing our hypothesis *H2* that IG bonds with high (low) systematic risk exposure are overpriced (underpriced). We do so by examining whether bonds with high (low) systematic risk exposure generate negative (positive) risk-adjusted returns. Specifically, at the end of each month t we sort all 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 then calculate the MV-weighted month $t+1$ excess returns for each portfolio. If high-systematic (low-systematic) risk bonds are overpriced (underpriced), as predicted by our hypothesis *H2*, the high-systematic (low-systematic) risk portfolio should generate negative (positive) alpha. To rigorously test for differential pricing between high-systematic and low-systematic risk bonds, we also calculate the excess returns for the zero-cost long-short portfolio that is long the decile 10 portfolio and short the decile one portfolio. Our hypothesis predicts that this long-short portfolio should generate a negative alpha.

Since our hypothesis *H2* is conditional on capital charge, we repeat our tests using portfolios that are constructed to be capital charge-neutral. Specifically, at the end of each month t, we first separate bonds into two groups based on their NAIC designation and repeat the portfolio analysis within each group. We then 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 two NAIC designation groups, and examine the performance of these portfolios. We refer to these analyses as conditional portfolio analyses and the analyses that do not condition on NAIC designation, described in the previous paragraph, as unconditional analyses.

4.2.1 Bond Market Risk Exposure and Bond Pricing

Our first tests of the relation between bond pricing and systematic risk exposure examine the performance of portfolios formed by sorting bonds on β^{CBMKT}. The results of these tests are presented in Table 5. 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 post-formation 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 $CBMKT$.[28] The slope coefficients from these regressions, reported in the rows labeled β^{CBMKT}_{Post}, demonstrate that our portfolio formation procedure works as intended. For the unconditional analyses, the post-formation exposures to $CBMKT$ increase monotonically from 0.36 for the decile one portfolio to 1.65 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 (β^{CBMKT} $10-1$) has a post-formation exposure to $CBMKT$ of 1.29 (t-statistic = 27.34). The results are similar for the conditional analyses. Consistent with the increasing pattern in bond market risk exposure, the average excess returns of the portfolios generally increase across the β^{CBMKT} deciles. Although both the unconditional and conditional analyses indicate that the average excess return of the β^{CBMKT} $10-1$ portfolio is positive, in both cases it is statistically insignificant.

Most importantly, the results in Table 5 provide strong evidence that bonds with high (low) $CBMKT$ exposure generate low (high) risk-adjusted returns, thus supporting our hypothesis that high-systematic (low-systematic) risk exposure bonds are overpriced (underpriced). 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 unconditional decile 1 portfolio generates a significantly positive alpha of 0.23% per month (t-statistic = 8.57) and the decile 10 portfolio generates a significantly negative alpha of -0.13% per month (t-statistic = -3.00).[29] The unconditional β^{CBMKT} $10-1$ portfolio generates a monthly alpha of -0.36% (t-statistic = -6.14). Results for the conditional portfolios are similar. For instance, the β^{CBMKT} $10-1$ portfolios produce alpha of -0.31% (t-statistic = -5.04) and -0.38% (t-statistic = -5.57) among NAIC designation 1 and 2 bonds, respectively. The β^{CBMKT} $10-1$ portfolio in the average NAIC designation group, therefore, generates a monthly alpha of -0.35% (t-statistic = -6.30). Each of these alphas is both economically large and highly statistically significant.

[28] We estimate post-formation exposure to $CBMKT$ using the one-factor model given by equation (2) because $CBMKT$ is not one of the factors in the model we use to evaluate risk-adjusted performance (equation (4)). Since by construction $CBMKT$ is a linear combination of $TERM$ and DEF, including $CBMKT$ in equation (4) would introduce multicolllinearity. 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 post-formation exposure would be the same as the one obtained from the one-factor model.

[29] To conserve space, in the main paper we present only the estimates of α from the factor regressions. The full set of estimated coefficients for each portfolio are discussed in Section VIII and shown in Table A38 of the Internet Appendix.

4.2.2 Term Factor Exposure and Bond Pricing

Table 6 presents the results of our analysis of portfolios formed by sorting on β^{TERM}. The results strongly support our hypothesis that bonds with high (low) term factor exposure are overpriced (underpriced). The decile 1 portfolios generate significantly positive alpha while the decile 10 portfolios generate negative and, with one exception, statistically significant alphas. The unconditional β^{TERM} $10-1$ portfolio generates alpha of -0.37% per month (t-statistic $= -5.99$). The conditional β^{TERM} $10-1$ portfolios generate monthly alphas of -0.37% (t-statistic $= -5.75$) among NAIC designation 1 bonds, -0.32% (t-statistic $= -4.16$) among NAIC designation 2 bonds, and -0.34% (t-statistic $= -5.77$) in the average NAIC designation group. The portfolios' post-formation 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 post-formation dispersion in term factor exposure. For both the unconditional and conditional portfolios, β^{TERM}_{Post} increases monotonically across the β^{TERM} deciles and the β^{TERM} $10-1$ portfolios have large and highly statistically significant positive β^{TERM}_{Post}.[30]

4.2.3 Default Factor Exposure and Bond Pricing

Finally, we investigate the hypothesis that bonds with high systematic default risk exposure are overpriced relative to bonds with low systematic default risk exposure by examining the risk-adjusted returns of portfolios formed by sorting on β^{DEF}. Table 7 shows that both the unconditional and conditional β^{DEF} portfolios have generally increasing post-formation exposure to default factor risk, and the β^{DEF} $10-1$ portfolios have an economically large and statistically significant positive β^{DEF}_{Post}. The alphas of the decile 1 portfolios are (with one exception) statisticially positive, but small, ranging from 0.07 to 0.12 per month, while those of the decile 10 portfolios are all very close to zero. The alphas of the β^{DEF} $10-1$ portfolios are all negative but 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.[31] 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 2). Analysis of insurer holdings in Section 5.1.1 supports this conjecture.

4.3 Persistence of Pricing Effects

As discussed in Van Binsbergen and Opp (2017), while the effects on the real economy of transient alpha generated by temporary price pressure are minimal, those of persistent alpha can be substantial. We therefore test whether the price patterns we detect are temporary or whether they reflect a

[30]To conserve space, in the main paper we present only the estimates of α and β^{TERM}_{Post} from the factor regressions. The full set of estimated coefficients for each portfolio are discussed in Section VIII and shown in Table A39 of the Internet Appendix.

[31]To conserve space, in the main paper we present only the estimates of α and β^{DEF}_{Post} from the factor regressions. The full set of estimated coefficients for each portfolio are discussed in Section VIII and shown in Table A40 of the Internet Appendix.

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 4.1 and 4.2, 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 8, 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 8 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 $t+1$.

5 Drivers of Bond Pricing Effects

Having demonstrated support for our bond pricing hypotheses *H1* and *H2*, we next investigate the drivers of the pricing patterns. We first test our hypothesis *H3* that the detected bond pricing patterns are attributable to insurer demand. We then turn to tests of our hypothesis *H4* that the driver of insurer demand, and thus of the pricing patterns, is rating-based capital requirements.

5.1 Insurer Demand and Bond Pricing

Our tests of *H3* require data on insurers' corporate bond holdings, which we gather from insurers' statutory filings with the NAIC for the 2002-2014 period. Schedule D Part 1 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 $\%InsHeld$ as the bond's par value held by all insurers scaled by the bond's contemporaneous par value outstanding, obtained from Mergent FISD (or Thomson Reuters SDC, if Mergent FISD data are missing), times 100 so the value represents a percentage. Since insurer holdings data from the NAIC are available at an annual frequency, $\%InsHeld$ is calculated each December and remains the same through the following November. Also, since the data start in 2002, the analyses in this section cover months t (return months $t+1$) from December 2002 (January 2003) through November (December) 2014, inclusive.

5.1.1 Insurer Holdings

We first examine 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 $\%InsHeld$ 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' investment 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 3), drive our results. The regressions are of the form:

$$\%InsHeld_{i,t} = \gamma_0 + \gamma_{BBB-}BBB-_{i,t} + \gamma_{\beta^j}\beta^j_{i,t} + \gamma_{NAIC2}NAIC2_{i,t} + \omega_{i,t} \quad (5)$$

where $BBB-$ equals one if the bond is rated BBB− and zero otherwise, β^j is either β^{CBMKT}, β^{TERM}, or β^{DEF}, and $NAIC2$ equals one for NAIC designation 2 bonds and zero otherwise. Regression specification (5) is not intended to be a complete model of insurer corporate bond holdings. The objective here is simply to 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 two ways. First, each month t we run cross-sectional bond-level regressions in the spirit of Fama and MacBeth (1973, FM hereafter). 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 zero. The results of these regressions, presented in columns (1)–(3) of Table 9, 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 three 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 to 8 percentage points less of the outstanding par value of BBB− bonds than of other NAIC designation 2 bonds. Specification (1) indicates that a one unit increase in bond market risk exposure is associated with insurers holding 10.03 percentage points (t-statistic = 13.04) more of the outstanding par value of the bond. For term factor exposure, this number increases to 35.69 percentage points (t-statistic = 25.45). 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 2), giving insurers less 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 4-8, 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 $\%InsHeld$ may result in correlated error terms and inflated t-statistics (Petersen (2009)), we estimate specification (5) as a panel regression with year fixed effects and standard errors clustered by time and rating. The results of these estimations, reported in columns (4)–(6) of Table 2, are similar to those of the FM regressions reported in columns (1)–(3).

5.1.2 Insurer Holdings and Bond Performance

Having demonstrated that insurers strongly tilt their corporate bond portfolios away from bonds with high NIG proximity and towards bonds with high systematic risk exposure, bond characteristics that our hypotheses link to investment incentives created by rating-based capital requirements, we next investigate whether insurers' demand for these bonds is the driver of the pricing patterns documented in Section 4. We do so by examining the relation between insurer holdings and risk-adjusted bond returns.

While 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. Such alpha-seeking behavior by insurers would suggest a positive, not a negative, relation between insurer holdings and future risk-adjusted bond returns. Our empirical tests, therefore, must be designed to measure the relation between future risk-adjusted returns and the component of insurers' demand that is not driven by alpha-seeking behavior. We therefore 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 two 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 insurers 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 9 indicate that insurers' demand for high-systematic risk bonds is particularly strong for bonds with high term factor risk exposure.[32] If, as our hypothesis *H3* predicts, insurers' demand drives the pricing patterns documented in Section 4, then the alphas of the 20 portfolios should be negatively related to insurer holdings.

[32] In Section IX and Table A41 of the Internet Appendix we demonstrate that our results are robust when we use other sets of IG bonds or β^{CBMKT} as the measure of systematic risk exposure.

Panel A of Table 10 presents the alphas for each of the 20 portfolios, as well as for the β^{TERM} $10-1$ portfolio in each NIG proximity group, and the [BBB−]−NAIC 2 No BBB− portfolio in each β^{TERM} group. The results indicate that the pricing patterns documented in Section 4 remain strong in the shortened 2003-2014 period. The average β^{TERM} $10-1$ portfolio generates large and highly significant monthly alpha of −0.44% (t-statistic=−5.06). Similarly, in the average β^{TERM} group, the alpha of the [BBB−]−NAIC 2 No BBB− portfolio is positive and significant.

We next calculate the proportion of the aggregate market value of all bonds in each portfolio that is held by insurers. Specifically, in any given month we define portfolio-level $\%InsHeld$ to be the MV-weighted average of bond-level $\%InsHeld$ across all bonds in that portfolio. Table 10 Panel B presents the time-series averages of the portfolio-level $\%InsHeld$ for each of the β^{TERM} and rating-based portfolios. The patterns are highly consistent with the results of the bond-level FM regressions reported in Table 9. In each β^{TERM} group, the average portfolio-level $\%InsHeld$ is substantially smaller for the BBB− portfolio than for the NAIC 2 No BBB− portfolio. Similarly, in both the BBB− group and the NAIC 2 No BBB− group, the average portfolio-level $\%InsHeld$ values of high-β^{TERM} portfolios are much higher than those of low-β^{TERM} portfolios.

We test the impact of insurer holdings on bond pricing in two ways.[33] First, we run a single regression of the 20 portfolio alphas from Table 10 Panel A on the corresponding average portfolio-level $\%InsHeld$ from Table 10 Panel B. The results of this regression, shown in column (1) of Table 11, strongly support our hypothesis that the pricing patterns we document earlier in the paper are driven by insurer demand, since the coefficient on the average portfolio-level $\%InsHeld$ 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 $\%InsHeld$ 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 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 $\%InsHeld$. The time-series averages of the monthly cross-sectional regression coefficients, shown in column (2) of Table 11, are consistent with the results of the single regression. The average coefficient on $\%InsHeld$ 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 $\%InsHeld$ 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

[33]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)).

holdings of unconstrained insurers. 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 $\%InsHeld_{Constrained}$ to be the percentage of its par value held by constrained insurers, and a bond's $\%InsHeld_{Unconstrained}$ as the difference $\%InsHeld - \%InsHeld_{Constrained}$. 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 $\%InsHeld_{Constrained}$ and $\%InsHeld_{Unconstrained}$ are then taken to be the MV-weighted averages of the corresponding bond-level values.

Since at the portfolio level $\%InsHeld_{Constrained}$ and $\%InsHeld_{Unconstrained}$ are highly correlated, to differentiate between their effect on bond pricing we also construct their orthogonalized versions. Specifically, we define a bond's $\%InsHeld_{Constrained,\perp}$ to be the residual from a bond-level cross-sectional regression of $\%InsHeld_{Constrained}$ on $\%InsHeld_{Unconstrained}$. Similarly, we define a bond's $\%InsHeld_{Unconstrained,\perp}$ to be the residual from a bond-level cross-sectional regression of $\%InsHeld_{Unconstrained}$ on $\%InsHeld_{Constrained}$. Portfolio-level $\%InsHeld_{Constrained,\perp}$ and $\%InsHeld_{Unconstrained,\perp}$ are calculated anologously to the other portfolio-level insurer holding measures.

Columns (3)-(10) of Table 11 present the results of the single and FM regressions of portfolio-level alphas on portfolio-level constrained and unconstrained insurer holdings. While both $\%InsHeld_{Constrained}$ (in columns (3) and (4)) and $\%InsHeld_{Unconstrained}$ (in columns (5) and (6)) have a strong and highly significant negative relation with alpha, the single-regression (FM-regression) coefficient on $\%InsHeld_{Constrained}$ of -0.048 (-0.041) is more than three times as large as the corresponding coefficient on $\%InsHeld_{Unconstrained}$ of -0.015 (-0.007). When both $\%InsHeld_{Constrained}$ and $\%InsHeld_{Unconstrained,\perp}$ are included in the same regression, the coefficient on $\%InsHeld_{Constrained}$ is nearly unchanged while the coefficient on $\%InsHeld_{Unconstrained,\perp}$ is statistically insignificant. Similarly, when $\%InsHeld_{Constrained,\perp}$ and $\%InsHeld_{Unconstrained}$ are included in the same regression, the coefficient on $\%InsHeld_{Constrained,\perp}$ is negative and highly statistically significant, while the coefficient on $\%InsHeld_{Unconstrained}$ is 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.

5.2 Insurers' Rating-Based Capital Requirements and Bond Pricing

Having attributed the bond pricing patterns to insurer demand, we turn to testing our last hypothesis *H4* that the driver of insurer demand, and thus of the pricing patterns, is rating-based capital requirements. 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. Additionally, 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.

Since insurer holdings data during and prior to the 1990s are unavailable, we are unable to investigate whether insurers' holdings are different in the period before compared to the period after the implementation of rating-based capital requirements. Instead, we test our hypothesis by examining whether the pricing patterns we attribute to insurer demand exist before the change in capital regulations. Specifically, we repeat each of the asset pricing tests of Section 4 using portfolio formation months t (return months $t+1$) from December 1977 (January 1978) through November (December) 1992. We choose the 1978-1992 period because bond return data are available starting in 1973, making December 1977 the first month for which β^{CBMKT}, β^{TERM}, and β^{DEF} can be calculated using a full 60 months of data. In the average month during the 1978-1992 period, our sample contains 3796 bonds, which is slightly larger than the 3405 bonds in the average month during the 1993-2014 period. The large number of bonds during the earlier period indicates that our tests should have sufficient power to detect a pricing effect, if one exists. As discussed in Section 2.1, we expect the frictionless benchmark to accurately characterize bond prices during the 1978-1992 period. The pricing tests should therefore not detect mispricing during this period.

The results of the portfolio analysis for the 1978-1992 period, shown in Table 12, 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 unconditional extreme beta decile portfolios, and the long-short (unconditional in the case of β^{CBMKT}-sorted, β^{TERM}-sorted, and β^{DEF}-sorted) portfolios examined earlier, with complete results provided in Section X and Tables A42-A45 of the Internet Appendix. 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 NAIC designation 1 bonds ([BBB−]−NAIC 1), NAIC designation 2 bonds not rated BBB− ([BBB−]−NAIC 2 No BBB−), IG bonds not rated BBB− ([BBB−]−IG No BBB−), or bond rated BBB ([BBB−]−BBB). These long-short portfolios generate economically small and statistically insignificant alphas. Similarly, the alphas of the beta-sorted extreme decile portfolios are small and, with the exception of the β^{CBMKT} and β^{TERM} decile 1 portfolios, statistically insignificant. The results provide no evidence that the unconditional 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. Importantly, since guaranty funds were in effect for the entirety of the 1978-1992 period, our results demonstrate that guaranty funds alone, which provide the incentive to increase risk-taking, are insufficient to generate mispricing related to systematic risk exposure. As discussed in our development of hypothesis *H2* (Section 2.2), it is the combination of guaranty funds and rating-based capital requirements that is ultimately responsible for the systematic-risk related pricing patterns we document.

The corresponding alphas from 1993-2014, previously shown in Tables 4, 5, 6, and 7 and repeated here for ease of comparison, suggest a difference in bond pricing patterns between the 1978-1992 and the 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 one for return months in 1993-2014 and to zero otherwise, and with this indicator's interaction with the factors. Table 12 presents the alphas from these regressions (complete results provided in Section X and Table A46 of the Internet Appendix), which indicate large and highly significant differences in bond pricing patterns during 1993-2014 compared to 1978-1992. For each NIG proximity-based portfolio, the coefficient on the 1993-2014 indicator, $\alpha_{1993-2014}$, is positive and statistically significant (marginally in the case of the BBB− and [BBB−]−NAIC 1 portfolios). The estimated alphas in the 1993-2014 period are between 0.14% and 0.16% per month higher than the corresponding alphas in the 1978-1992 period. For β^{CBMKT} and β^{TERM}, the alphas of the decile 1 (decile 10) portfolios are significantly higher (lower) for 1993-2014 than for 1978-1992. The alphas of the β^{CBMKT} $10-1$ and β^{TERM} $10-1$ portfolios during the 1993-2014 period are 0.31% per month lower than the corresponding alphas during the 1978-1992 period. As expected, given that the β^{DEF} $10-1$ portfolio does not generate significant alpha during the 1993-2014 period (see Table 7) and insurers do not appear to have excess demand for bonds with large default factor exposure (see Table 9), we find no evidence of a change in the pricing of the β^{DEF} portfolios after the implementation of rating-based capital requirements. The results in Table 12 demonstrate 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 before they are implemented.

5.3 Alternative Explanations for the Pricing Effects

The results in Sections 5.1 and 5.2 provide strong evidence that demand by insurers, induced by rating-based capital requirements, is the driver of the bond pricing effects we document. Here, we discuss several potential alternative explanations and argue that they are unlikely to drive these pricing effects.

5.3.1 Demand by Other Market Participants

While we argue that the pricing effects we document are due to demand by insurers, it is conceivable that demand by other investor groups, i.e., banks, pension funds, mutual funds, and/or exchange traded funds (ETFs), is responsible for our findings. For an explanation based on demand by another group of investors to be plausible, three conditions must be met. First, the investors must have a large enough presence in the corporate bond market to affect prices. Second, the investors must face investment incentives consistent with the observed pricing effects. Third, the investors must have investment incentives that change substantially around 1993. Below we explain why these three conditions are unlikely to be met by any corporate bond market investors other than insurers.

Similar to insurers, banks that are subject to rating-based capital charges that increase substantially for NIG bonds might have an incentive to avoid bonds with high NIG proximity. As discussed in Pennacchi (2006) and Iannotta et al. (2018), when combined with liability guarantees (e.g., deposit insurance), these capital requirements also provide an incentive for banks to tilt their investment portfolios towards high-systematic risk bonds. However, it is unlikely that banks alone are responsible for the pricing effects we document for the following reasons. First, during 1993-2014, banks hold only 6-16% of corporate bonds outstanding, compared to 29-38% for insurers (see Figure 1). Therefore, investment demand from banks is likely to have less of an impact on corporate bond prices than demand from insurers. Second, corporate bonds represent only 4%-10% of banks' investment portfolios during 1993-2014.[34] As a result, measures of bank capital adequacy are unlikely to be significantly affected by corporate-bond capital charges, thus making banks' incentives to overweight or underweight certain bonds relatively weak. Finally, rating-based capital requirements for banks are introduced through the implementation of Basel II in 2007, and become effective in 2008.[35] Since the pricing effects are present during the 1993-2007 period (see Section XI and Tables A47-A50 of the Internet Appendix), it is unlikely that demand from banks explains these effects, though it may be a contributing influence in the last few years of our sample period. The presence of the pricing effects during the 1993-2007 period also indicates that they are not due to the Dodd-Frank Act, which was signed into law in 2010.

Like insurers' capital requirements, investment guidelines for pension funds, mutual funds, and ETFs (collectively asset managers) also make use of credit ratings and often distinguish between IG and NIG bonds (e.g., Baghai, Becker, and Pitschner (2019)). This may create an incentive for asset managers to avoid high NIG-proximity bonds. However, unlike insurers that incur the cost of higher capital charges if they retain bonds downgraded to NIG, asset managers face no strong incentive to quickly sell such bonds and are rarely required to do so. A survey of 200 asset managers by Cantor et al. (2007) finds that only 4% are required to take action if a bond is downgraded and no longer meets the fund's retention/eligibility requirements. Thus, since asset managers have no strong aversion to purchasing bonds with high NIG proximity, the underpricing of these bonds is unlikely to be due to asset managers' demand. Asset managers also have little incentive to tilt their portfolios towards bonds with high systematic risk exposure because, unlike insurers, they are typically evaluated on a risk-adjusted basis (Becker and Ivashina (2015)). It is therefore unlikely that demand from asset managers drives the relative overpricing (underpricing) of high-systematic (low-systematic) risk exposure bonds. Finally, to the best of our knowledge there have been no

[34]Statistics are based on data from the Federal Reserve Statistical Release Z.1, Financial Accounts of the United States.

[35]Bank capital requirements became risk-based with Basel I, which was issued in 1988 and implemented in the U.S. by the end of 1992. However, risk weights under Basel I did not differentiate between the degrees of risk within corporate debt, most of which carried a risk weight of 100%. The implementation of Basel I therefore provided no incentives for banks to underweight high-NIG proximity bonds or overweight (underweight) bonds with high-systematic (low-systematic) risk exposure.

regulatory or market changes in or around 1993 that would have caused a shift in asset managers' investment demand. This makes it difficult to reconcile the absence of the documented pricing effect during 1978–1992 with an explanation based on asset managers' rating-based investment guidelines.

5.3.2 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. 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 mispricing to exist, we conduct Gibbons, Ross, and Shanken (1989, GRS hereafter) 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 XII and Table A51 of the Internet Appendix, we show that the GRS tests fail to reject this null hypothesis. Finally, as discussed in Sections II-V and Tables A6-A29 of the Internet Appendix, our results are robust when using several different factor models and alternative definitions for the $CBMKT$, $TERM$, and DEF factors. Our findings also remain unchanged when we add an aggregate bond liquidity risk factor to our model or use the broker-dealer leverage factor of Adrian et al. (2014).

6 Conclusion

In this paper, we show that rating-based capital requirements, through their impact on investment demand, affect equilibrium market prices. Specifically, we document two patterns in corporate bond prices and attribute them to demand induced by rating-based capital requirements. First, we demonstrate that IG bonds with high NIG proximity generate positive risk-adjusted returns, indicating that high-NIG proximity bonds are underpriced. Second, we show that bonds with high (low) systematic risk exposure generate negative (positive) risk-adjusted returns, meaning that high-systematic (low-systematic) risk exposure bonds are overpriced (underpriced). These pricing patterns are persistent across a large cross-section and long time-series of more than 20,000 corporate bonds over the 1993-2014 time period.

We then attribute these patterns in bond prices to insurer demand and in turn to rating-based capital requirements. Our results demonstrate that insurers do indeed invest proportionally less in high NIG proximity bonds and proportionally more (less) in bonds with high (low) systematic risk exposure. These patterns in insurer holdings explain most of the patterns in bond pricing. Finally, we tie the patterns in bond pricing to capital regulations by showing that the patterns do not exist prior to the implementation of rating-based capital requirements for insurers in 1993.

Our paper 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 (Stein (1996), Chirinko and Schaller (2001), Baker et al. (2003), Gilchrist et al. (2005), Polk and Sapienza (2009), Harford et al. (2015), and Warusawitharana and Whited (2016)), our results provide a clear link between capital regulations and real economic outcomes. Because persistent alphas are known to have greater implications for corporate investment than transient alphas (Van Binsbergen and Opp (2017)), 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. The Financial Stability Oversight Council has designated several insurers as systemically important financial institutions in part because of a concern that their interconnectedness 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 pro-cyclicality of real investment. Enhanced 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.

References

Acharya, Viral V., Yakov Amihud, and Sreedhar T. Bharath, 2013, Liquidity risk of corporate bond returns: conditional approach, *Journal of Financial Economics* 110, 358–386.

Acharya, Viral V., and Matthew Richardson, 2009, Causes of the financial crisis, *Critical Review* 21, 195–210.

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557–2596.

Ambrose, Brent W., Nianyun (Kelly) Cai, and Jean Helwege, 2008, Forced selling of fallen angels, *Journal of Fixed Income* 18, 72–85.

Baghai, Ramin P., Bo Becker, and Stefan Pitschner, 2019, The private use of credit ratings: evidence from investment mandates, Working paper available at http://ssrn.com/abstract=3201006.

Bai, Jennie, Turan G. Bali, and Quan Wen, 2018, Common risk factors in the cross-section of corporate bond returns, *Journal of Financial Economics* forthcoming.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the market matter? Stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* 118, 969–1005.

Becker, Bo, and Victoria Ivashina, 2015, Reaching for yield in the bond market, *Journal of Finance* 70, 1863–1902.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds, *Journal of Financial Economics* 82, 251–288.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–455.

Bongaerts, Dion, Frank de Jong, and Joost Driessen, 2017, An asset pricing approach to liquidity effects in corporate bond markets, *Review of Financial Studies* 30, 1229–1269.

Calomiris, Charles W., and Joseph R. Mason, 2010, Conflicts of interest, low-quality ratings, and meaningful reform of credit and corporate governance ratings, E21 Report, Manhattan Institute for Policy Research.

Cantor, Richard, Owain ap Gwilym, and Stephen Thomas, 2007, The use of credit ratings in investment management in the U.S. and Europe, *Journal of Fixed Income* 17, 13–26.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chirinko, Robert S., and Huntley Schaller, 2001, Business fixed investment and "bubbles": the Japanese case, *American Economic Review* 91, 663–680.

Choi, Jaewon, and Yongjun Kim, 2018, Anomalies and market (dis) integration, *Journal of Monetary Economics* forthcoming.

Chordia, Tarun, Amit Goyal, Yoshio Nozawa, Avanidhar Subrahmanyam, and Qing Tong, 2017, Are capital market anomalies common to equity and corporate bond markets? An empirical investigation, *Journal of Financial and Quantitative Analysis* 52, 1301–1342.

Cornaggia, Jess, Kimberly J. Cornaggia, and John E. Hund, 2017, Credit ratings across asset classes: a long-term perspective, *Review of Finance* 21, 1–45.

Crawford, Steve, Pietro Perotti, Richard A. Price, and Christopher J. Skousen, 2015, Accounting-based anomalies in the bond market, Working paper available at http://ssrn.com/abstract=2423850.

Cummins, J. David, 1988, Risk-based premiums for insurance guaranty funds, *Journal of Finance* 43, 823–839.

Dick-Nielsen, Jens, 2009, Liquidity biases in TRACE, *Journal of Fixed Income* 19, 43–55.

Dick-Nielsen, Jens, 2014, How to clean Enhanced TRACE, Working paper available at http://ssrn.com/abstract=2337908.

Dick-Nielsen, Jens, Peter Feldhütter, and David Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103, 471–492.

Duncan, Michael P., 1984, An appraisal of property and casualty post-assessment guaranty funds, *Journal of Insurance Regulation* 3, 289–303.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

Ellul, Andrew, Chotibhak Jotikasthira, Christian T. Lundblad, and Yihui Wang, 2015, Is historical cost accounting a panacea? Market stress, incentive distortions, and gains trading, *Journal of Finance* 70, 2489–2537.

Eom, Young Ho, Jean Helwege, and Jing-Zhi Huang, 2004, Structural models of corporate bond pricing: an empirical analysis, *Review of Financial Studies* 17, 499–544.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81, 607–636.

Frazzini, Andrea, and Lasse H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Gebhardt, William R., Søeren Hvidkjær, and Bhaskaran Swaminathan, 2005, The cross-section of expected corporate bond returns: betas or characteristics?, *Journal of Financial Economics* 75, 85–114.

Gibbons, Michael R, Stephen A Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Gilchrist, Simon, Charles P. Himmelberg, and Gur Huberman, 2005, Do stock price bubbles influence corporate investment?, *Journal of Monetary Economics* 52, 805–827.

Gompers, Paul, and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–259.

Grace, Martin F, Scott E Harrington, and Robert W Klein, 1998, Risk-based capital and solvency screening in property-liability insurance: hypotheses and empirical tests, *Journal of Risk and Insurance* 65, 213–243.

Harford, Jarrad, Marc Martos-Vila, and Matthew Rhodes-Kropf, 2015, Corporate financial policies in overvalued credit markets, Working paper available at http://ssrn.com/abstract=2200093.

Harris, Milton, Christian C. Opp, and Marcus M. Opp, 2017, Bank capital and the composition of credit, Working paper available at https://ssrn.com/abstract=2467761.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–770.

Iannotta, Giuliano, George Pennacchi, and João Santos, 2018, Ratings-based regulation and systematic risk incentives, *Review of Financial Studies* forthcoming.

Ivashina, Victoria, and Zheng Sun, 2011, Institutional demand pressure and the cost of corporate loans, *Journal of Financial Economics* 99, 500–522.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W. Stahel, 2013, Momentum in corporate bond returns, *Review of Financial Studies* 26, 1649–1693.

Kisgen, Darren J., and Philip E. Strahan, 2010, Do regulations based on credit ratings affect a firm's cost of capital?, *Review of Financial Studies* 23, 4324–4347.

Koijen, Ralph, and Motohiro Yogo, 2016, An equilibrium model of institutional demand and asset prices, Working paper available at https://ssrn.com/abstract=2537559.

Lando, David, and Torben M. Skødeberg, 2002, Analyzing rating transitions and rating drift with continuous observations, *Journal of Banking and Finance* 26, 423–444.

Lee, Soon-Jae, David Mayers, and Clifford W. Smith, 1997, Guarantee funds and risk-taking: Evidence from the insurance industry, *Journal of Financial Economics* 44, 3–24.

Lin, Hai, Junbo Wang, and Chunchi Wu, 2011, Liquidity risk and expected corporate bond returns, *Journal of Financial Economics* 99, 628–650.

Munch, Patricia, and Dennis E. Smallwood, 1979, Solvency regulation in the property/casualty insurance industry, The Rand Corporation.

Munch, Patricia, and Dennis E. Smallwood, 1980, Solvency regulation in the property-liability insurance industry: empirical evidence, *The Bell Journal of Economics* 11, 261–279.

Nanda, Vikram K., Wei Wu, and Xing (Alex) Zhou, 2017, Investment commonality across insurance companies: fire sale risk and corporate yield spreads, Working paper available at https://ssrn.com/abstract=2995872.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

O'Hara, Maureen, Yihui Wang, and Xing (Alex) Zhou, 2018, The execution quality of corporate bonds, *Journal of Financial Economics* forthcoming.

Opp, Christian C., Marcus M. Opp, and Milton Harris, 2013, Rating agencies in the face of regulation, *Journal of Financial Economics* 108, 46–61.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Pennacchi, George, 2006, Deposit insurance, bank regulation, and financial system risks, *Journal of Monetary Economics* 53, 1–30.

Petersen, Mitchell A, 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of Financial Studies* 22, 435–480.

Polk, Christopher, and Paola Sapienza, 2009, The stock market and corporate investment: a test of catering theory, *Review of Financial Studies* 22, 187–217.

Shleifer, Andrei, 1986, Do demand curves for stocks slope down?, *Journal of Finance* 41, 579–590.

Stanton, Richard, and Nancy Wallace, 2018, CMBS subordination, ratings inflation, and regulatory-capital arbitrage, *Financial Management* 47, 175–201.

Stein, Jeremy C., 1996, Rational capital budgeting in an irrational world, *Journal of Business* 69, 429–455.

Towns, John, Timothy Cockerill, Maytal Dahan, Ian Foster, Kelly Gaither, Andrew Grimshaw, Victor Hazlewood, Scott Lathrop, Dave Lifka, Gregory D Peterson, et al., 2014, XSEDE: accelerating scientific discovery, *Computing in Science & Engineering* 16, 62–74.

Van Binsbergen, Jules H., and Christian C. Opp, 2017, Real anomalies, Working paper available at https://ssrn.com/abstract=2747739.

Warga, Arthur D., 1991, Corporate bond price discrepancies in the dealer and exchange markets, *Journal of Fixed Income* 1, 7–16.

Warusawitharana, Missaka, and Toni M. Whited, 2016, Equity market misvaluation, financing, and investment, *Review of Financial Studies* 29, 603–654.

White, Lawrence J., 2010, Markets: the credit rating agencies, *Journal of Economic Perspectives* 24, 211–226.

Figure 1: Investors in the Corporate Bond Market

This figure 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.

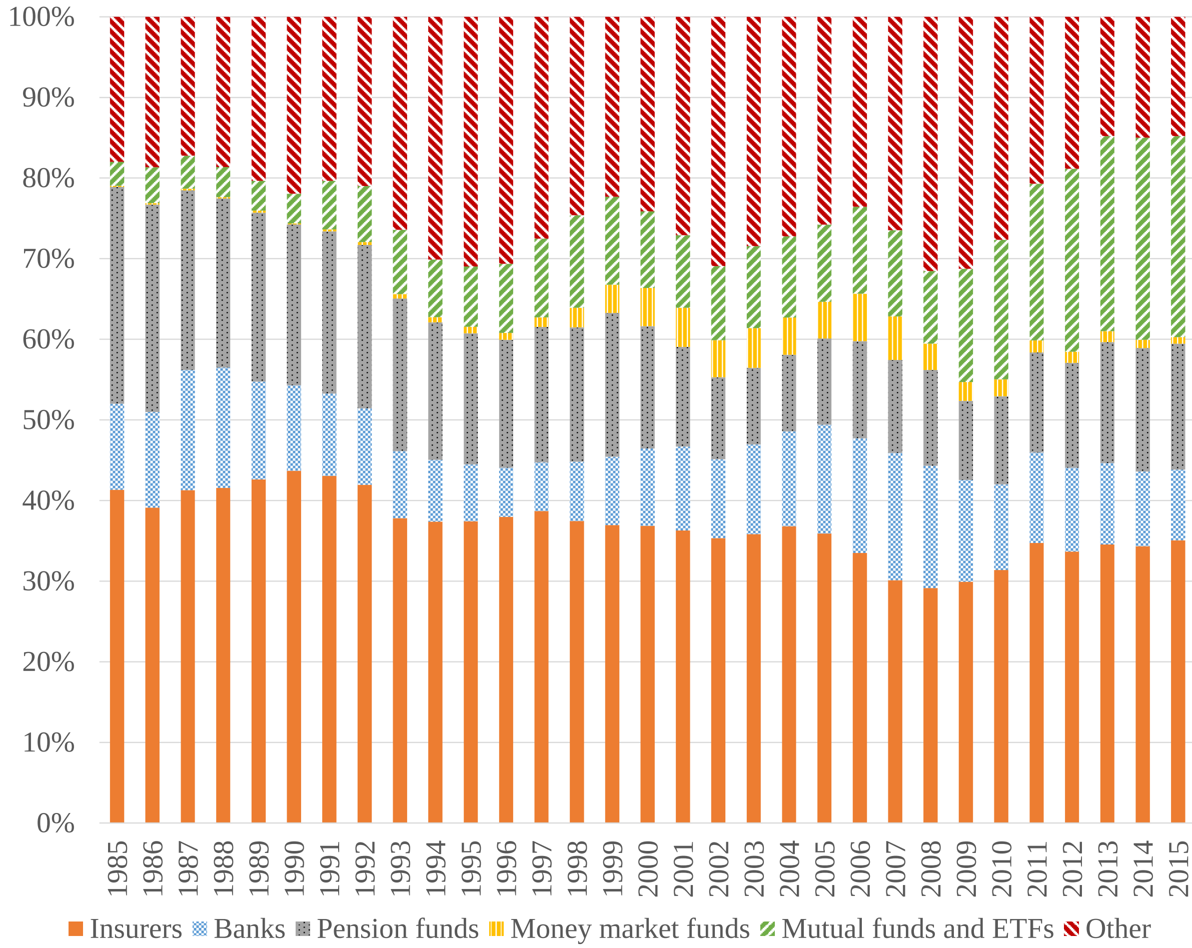

Figure 2: Insurer Portfolio Composition

This figure presents the combined portfolio composition of 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.

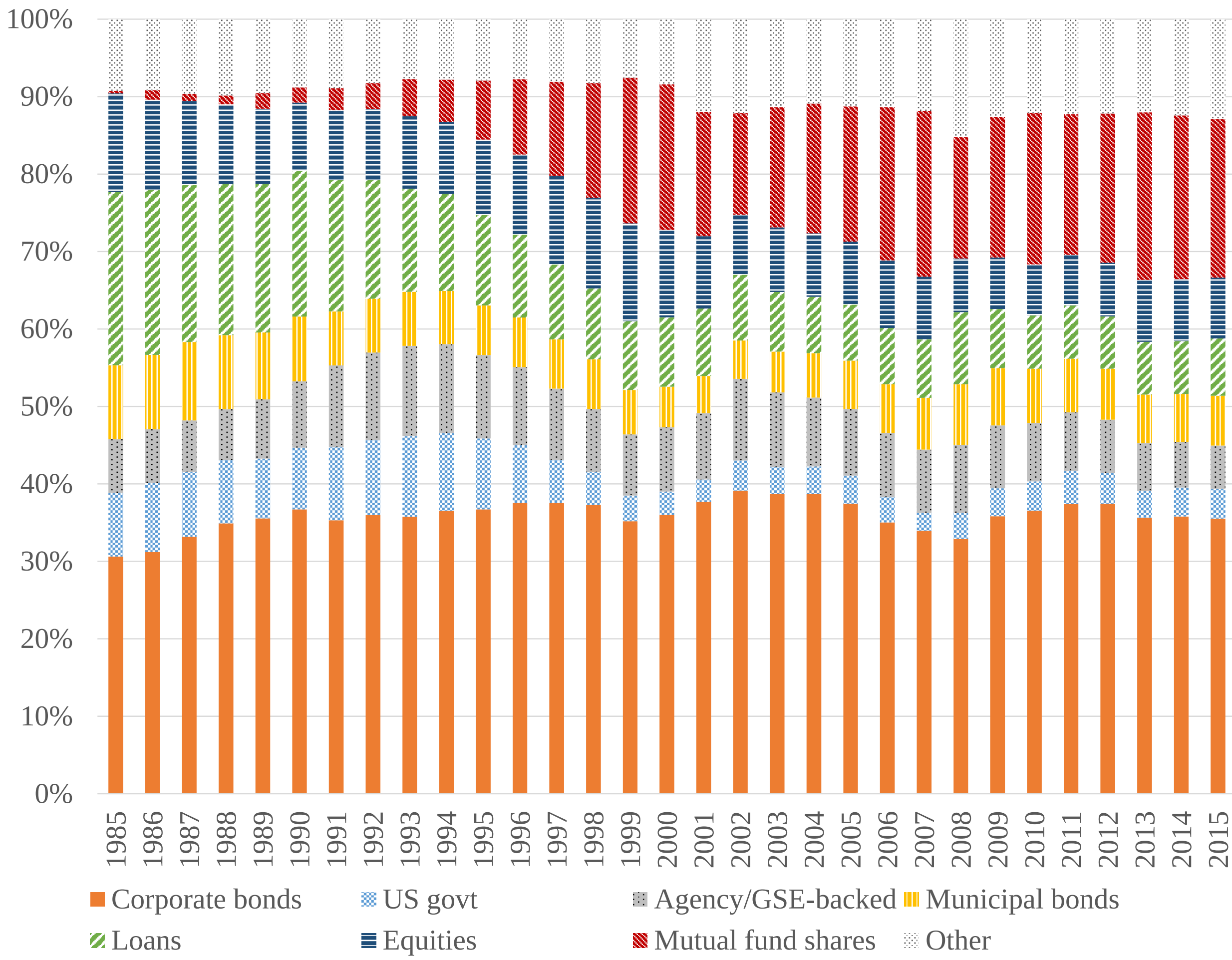

Figure 3: NIG Downgrades by Regulatory Rating

This figure presents the average percentage of bonds, by regulatory rating, that are downgraded to NIG. A bond's regulatory rating is its credit rating for regulatory capital purposes. For securities rated by multiple CRPs, the regulatory rating is the lower rating when two ratings are available and the second lowest rating when more than two ratings are available. 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 December 1992 to k months prior to December 2014, inclusive.

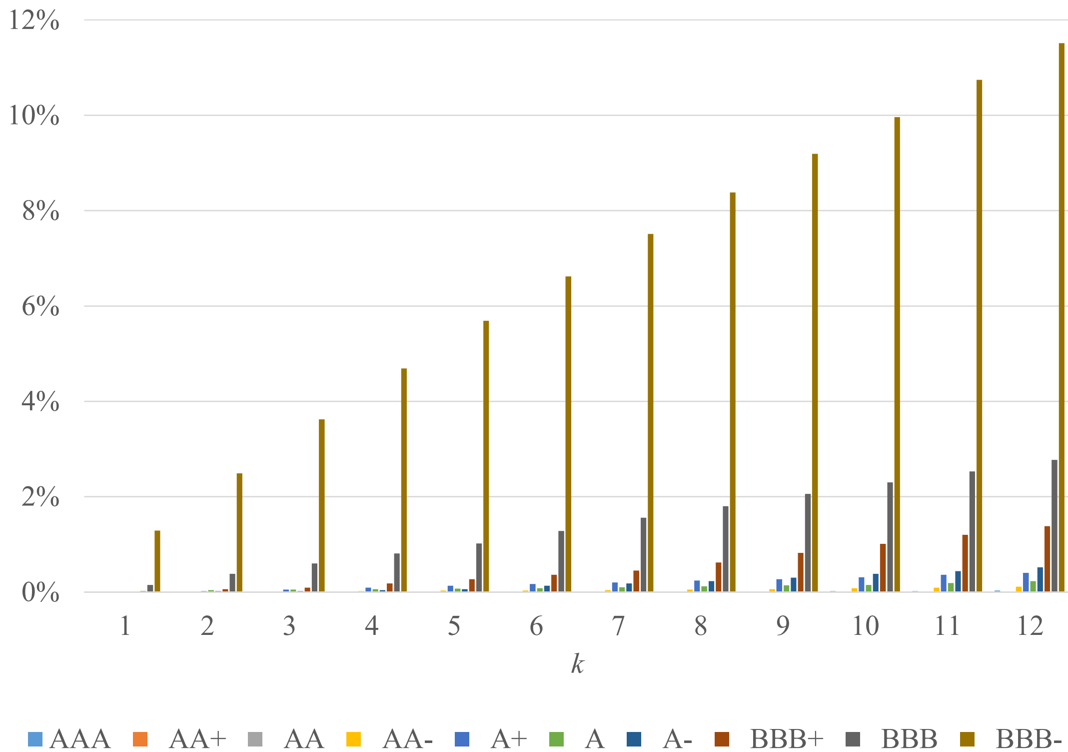

Table 1: Regulatory Ratings and Required Capital Charges for Corporate Bonds
This table presents the mapping of corporate bonds' regulatory rating to grade, NAIC designation, and required capital charge. Regulatory rating is the credit rating for regulatory capital purposes. For bonds rated by multiple CRPs, the regulatory rating is the lower rating when two are available and the second lowest rating when more than two are available. We use the S&P/Fitch rating scale without loss of generality. Grade indicates whether a bond with the given regulatory rating is investment grade (IG) or non-investment-grade (NIG). Columns labeled Life (P&C) give required capital charges for life (property/casualty) insurers.

		NAIC	Required Capital Charge	
Regulatory Rating	Grade	Designation	Life	P&C
A- and above	IG	1	0.4%	0.3%
BBB+, BBB, BBB−	IG	2	1.3%	1.0%
BB+, BB, BB−	NIG	3	4.6%	2.0%
B+, B, B−	NIG	4	10.0%	4.5%
CCC+, CCC, CCC−	NIG	5	23.0%	10.0%
CC, C, D	NIG	6	30.0%	30.0%

Table 2: Factor Summary Statistics
This table presents summary statistics and correlations for the monthly excess returns of corporate bond factors. $CBMKT$ is the market value-weighted average excess return of the bonds in our return data. $TERM$ is the Barclays Long Maturity U.S. Treasury index return minus the one-month U.S. Treasury bill return. DEF is the component of $CBMKT$ that is orthogonal to $TERM$. Returns are in percent. Panel A shows the time-series mean (Mean), standard deviation (SD), minimum (Min), first percentile (1%), fifth percentile (5%), 25th percentile (25%), median (Median), 75th percentile (75%), 95th percentile (95%), 99th percentile (99%), and maximum (Max) for each time-series. Panel B shows Pearson product-moment correlations. The summary statistics and correlations cover returns from January 1993 through December 2014, inclusive. Values of DEF are taken to be the intercept term plus the residual from a regression of $CBMKT$ on $TERM$ using data from this same period.

Panel A: Summary Statistics

Factor	Mean	SD	Min	1%	5%	25%	Median	75%	95%	99%	Max
$CBMKT$	0.35	1.28	−3.60	−3.29	−1.83	−0.42	0.40	1.06	2.39	3.00	5.44
$TERM$	0.47	2.84	−9.01	−5.89	−3.78	−1.35	0.48	2.15	4.58	8.96	12.27
DEF	0.21	0.95	−3.67	−2.57	−1.16	−0.23	0.20	0.71	1.73	2.90	4.04

Panel B: Correlations

	$TERM$	DEF
$CBMKT$	0.67	0.74
$TERM$		0.00

Table 3: Bond Summary Statistics

This table 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 $t-59$ through t, inclusive. MV is the par value outstanding times the market price of the bond per dollar of par, recorded in \$millions. 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 one-month U.S. Treasury bill return, recorded in percent. 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 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 December 1992 (January 1993) to November (December) 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

Table 4: Performance of Portfolios Sorted on NIG Proximity - 1993-2014

This table presents the results of a portfolio analysis examining the performance of portfolios formed by sorting on NIG proximity. At the end of each month t, all bonds are sorted into five portfolios based on whether they have (1) an NAIC designation of 1 (NAIC 1), (2) an NAIC designation of 2 but not a BBB− rating (NAIC 2 No BBB−), (3) an IG rating but not a BBB− rating (IG No BBB−), (4) a BBB rating (BBB), or (5) 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 four 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 post-formation 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 three 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 percent per month. The analysis covers portfolio formation (return) months t ($t+1$) from December 1992 (January 1993) to November (December) 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	0.38	0.34	0.40	0.48	0.16	0.11	0.14	0.08
	(4.14)	(4.65)	(4.39)	(4.88)	(5.71)	(3.24)	(2.71)	(3.35)	(2.06)
α	−0.01	0.02	−0.00	0.05	0.13	0.14	0.12	0.14	0.09
	(−0.45)	(0.67)	(−0.17)	(1.67)	(3.07)	(2.86)	(2.92)	(3.14)	(2.10)
β_{Post}^{TERM}	0.30	0.30	0.30	0.29	0.23	−0.07	−0.06	−0.07	−0.06
	(15.34)	(13.58)	(15.11)	(13.07)	(8.94)	(−4.21)	(−4.84)	(−4.51)	(−4.18)
β_{Post}^{DEF}	0.90	0.97	0.93	0.99	1.05	0.14	0.08	0.12	0.06
	(47.21)	(37.55)	(67.76)	(37.64)	(24.45)	(2.89)	(2.08)	(2.80)	(1.42)
$\beta_{Post}^{STOCKMKT}$	−0.02	0.01	−0.01	−0.01	0.02	0.03	0.01	0.02	0.03
	(−3.49)	(0.99)	(−1.84)	(−1.39)	(1.37)	(2.53)	(0.85)	(1.97)	(2.30)
β_{Post}^{SMB}	0.00	0.01	0.01	0.00	0.00	−0.00	−0.00	−0.00	0.00
	(0.80)	(0.64)	(1.22)	(0.23)	(0.24)	(−0.09)	(−0.16)	(−0.15)	(0.11)
β_{Post}^{HML}	−0.00	0.01	0.00	−0.00	−0.01	−0.01	−0.02	−0.01	−0.01
	(−0.33)	(1.49)	(0.73)	(−0.17)	(−0.60)	(−0.40)	(−1.64)	(−0.84)	(−0.51)
β_{Post}^{MOM}	0.01	−0.00	0.00	0.00	−0.01	−0.01	−0.00	−0.01	−0.01
	(2.25)	(−0.33)	(1.31)	(0.88)	(−0.70)	(−1.47)	(−0.54)	(−1.12)	(−1.28)
β_{Post}^{LIQ}	−0.01	0.01	−0.00	0.01	0.02	0.03	0.01	0.02	0.02
	(−2.09)	(1.89)	(−0.19)	(1.04)	(2.18)	(2.70)	(1.14)	(2.25)	(1.58)

Table 5: Performance of Portfolios Sorted on β^{CBMKT} - 1993-2014

This table presents the results of analyses examining the performance of portfolios formed by sorting on β^{CBMKT}. For the unconditional portfolio analysis, at the end of each month t, all bonds are sorted into decile portfolios based on an ascending ordering of β^{CBMKT}. 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 (β^{CBMKT} $10-1$). For the conditional portfolio analysis, at the end of each month t, all bonds are sorted into two 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}. 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 (β^{CBMKT} $10-1$) in each NAIC designation group. Finally, for each β^{CBMKT} decile portfolio as well as the β^{CBMKT} $10-1$ portfolio, we calculate the average excess return across the two NAIC designation groups, and refer to this as the NAIC Avg. group. The rows labeled β^{CBMKT}_{Post} present the slope coefficient from a regression of excess portfolio returns on $CBMKT$. 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 three lags and testing the null hypothesis of a zero post-formation exposure to bond market risk, a zero mean excess return, and a zero alpha, are shown in parentheses. Excess returns and alphas are in percent per month. The analysis covers portfolio formation (return) months t ($t+1$) from December 1992 (January 1993) to November (December) 2014, inclusive.

	Value	β^{CBMKT} 1	β^{CBMKT} 2	β^{CBMKT} 3	β^{CBMKT} 4	β^{CBMKT} 5	β^{CBMKT} 6	β^{CBMKT} 7	β^{CBMKT} 8	β^{CBMKT} 9	β^{CBMKT} 10	β^{CBMKT} $10-1$
Unconditional	β^{CBMKT}_{Post}	0.36	0.54	0.64	0.75	0.79	0.96	1.06	1.18	1.39	1.65	1.29
		(17.74)	(22.55)	(20.75)	(32.84)	(30.30)	(39.28)	(43.98)	(46.65)	(49.84)	(46.45)	(27.34)
	Excess Return	0.34	0.22	0.27	0.28	0.25	0.36	0.39	0.41	0.47	0.48	0.14
		(8.97)	(4.27)	(4.23)	(4.28)	(3.51)	(4.39)	(4.41)	(4.21)	(4.06)	(3.52)	(1.19)
	α	0.23	0.04	0.04	0.02	−0.02	0.02	0.03	−0.00	−0.03	−0.13	−0.36
		(8.57)	(1.13)	(0.88)	(0.56)	(−0.51)	(0.49)	(0.92)	(−0.11)	(−0.77)	(−3.00)	(−6.14)
NAIC 1	β^{CBMKT}_{Post}	0.36	0.53	0.63	0.75	0.81	0.99	1.10	1.19	1.43	1.64	1.28
		(18.12)	(22.99)	(23.40)	(29.36)	(24.38)	(34.69)	(42.19)	(40.65)	(42.18)	(40.59)	(25.71)
	Excess Return	0.29	0.23	0.26	0.26	0.25	0.34	0.37	0.38	0.46	0.46	0.18
		(7.60)	(4.54)	(4.24)	(3.86)	(3.29)	(3.90)	(3.96)	(3.77)	(3.78)	(3.34)	(1.49)
	α	0.17	0.05	0.05	0.00	−0.01	−0.01	0.00	−0.04	−0.04	−0.14	−0.31
		(6.70)	(1.79)	(1.39)	(0.13)	(−0.30)	(−0.18)	(0.12)	(−0.98)	(−0.91)	(−2.79)	(−5.04)
NAIC 2	β^{CBMKT}_{Post}	0.37	0.55	0.64	0.74	0.75	0.92	0.97	1.19	1.36	1.67	1.30
		(13.65)	(14.13)	(19.41)	(18.99)	(20.92)	(34.35)	(21.66)	(29.85)	(32.87)	(40.19)	(24.31)
	Excess Return	0.40	0.27	0.31	0.30	0.26	0.38	0.45	0.46	0.48	0.55	0.15
		(8.83)	(4.19)	(4.61)	(3.92)	(3.45)	(4.67)	(4.74)	(4.30)	(4.03)	(3.84)	(1.20)
	α	0.28	0.07	0.07	0.02	−0.02	0.03	0.09	0.03	−0.02	−0.10	−0.38
		(7.84)	(1.41)	(1.52)	(0.29)	(−0.39)	(0.78)	(1.42)	(0.47)	(−0.34)	(−1.83)	(−5.57)
NAIC Avg.	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)

Table 6: Performance of Portfolios Sorted on β^{TERM} - 1993-2014

This table presents the results of analyses examining the performance of portfolios formed by sorting on β^{TERM}. For the unconditional portfolio analysis, at the end of each month t, all bonds are sorted into decile portfolios based on an ascending ordering of β^{TERM}. 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 (β^{TERM} $10-1$). For the conditional portfolio analysis, at the end of each month t, all bonds are sorted into two 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^{TERM}. 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 (β^{TERM} $10-1$) in each NAIC designation group. Finally, for each β^{TERM} decile portfolio as well as the β^{TERM} $10-1$ portfolio, we calculate the average excess return across the two NAIC designation groups, and refer to this as the NAIC Avg. group. The rows labeled β^{TERM}_{Post} and α present the intercept coefficient and slope coefficient on $TERM$, respectively, from a regression of 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. The rows labeled Excess Return present the time-series average of the monthly excess returns. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero post-formation exposure to term factor risk, a zero mean excess return, and a zero alpha, are shown in parentheses. Excess returns and alphas are in percent per month. The analysis covers portfolio formation (return) months t ($t+1$) from December 1992 (January 1993) to November (December) 2014, inclusive.

	Value	β^{TERM} 1	β^{TERM} 2	β^{TERM} 3	β^{TERM} 4	β^{TERM} 5	β^{TERM} 6	β^{TERM} 7	β^{TERM} 8	β^{TERM} 9	β^{TERM} 10	β^{TERM} $10-1$
Unconditional	β^{TERM}_{Post}	0.08	0.14	0.18	0.21	0.25	0.31	0.35	0.43	0.52	0.67	0.59
		(4.09)	(7.90)	(10.43)	(9.74)	(12.35)	(13.11)	(14.81)	(16.27)	(17.92)	(21.59)	(25.30)
	Excess Return	0.38	0.32	0.29	0.30	0.32	0.36	0.37	0.41	0.45	0.47	0.09
		(6.54)	(5.88)	(4.88)	(4.24)	(4.33)	(4.18)	(4.08)	(3.93)	(3.62)	(3.19)	(0.71)
	α	0.21	0.12	0.05	0.03	0.02	−0.01	−0.03	−0.04	−0.09	−0.16	−0.37
		(5.91)	(4.42)	(1.65)	(0.91)	(0.72)	(−0.18)	(−0.87)	(−1.00)	(−2.55)	(−3.30)	(−5.99)
NAIC 1	β^{TERM}_{Post}	0.08	0.15	0.18	0.22	0.26	0.33	0.37	0.45	0.55	0.69	0.61
		(4.24)	(9.07)	(10.27)	(9.51)	(11.39)	(13.70)	(14.31)	(16.32)	(18.14)	(22.61)	(25.03)
	Excess Return	0.32	0.29	0.27	0.27	0.31	0.35	0.35	0.42	0.43	0.42	0.10
		(5.63)	(5.34)	(4.60)	(3.59)	(3.97)	(3.92)	(3.58)	(3.82)	(3.31)	(2.84)	(0.81)
	α	0.17	0.10	0.05	0.03	0.01	−0.03	−0.06	−0.04	−0.13	−0.19	−0.37
		(4.62)	(3.30)	(1.66)	(0.53)	(0.28)	(−0.80)	(−1.53)	(−0.92)	(−3.28)	(−3.66)	(−5.75)
NAIC 2	β^{TERM}_{Post}	0.07	0.14	0.18	0.19	0.24	0.27	0.33	0.39	0.50	0.63	0.56
		(3.04)	(6.23)	(8.22)	(8.79)	(11.00)	(9.80)	(13.59)	(13.09)	(15.72)	(18.71)	(20.54)
	Excess Return	0.43	0.38	0.32	0.33	0.33	0.41	0.36	0.43	0.48	0.55	0.12
		(6.39)	(5.70)	(4.58)	(4.59)	(4.50)	(4.43)	(3.96)	(4.01)	(3.81)	(3.78)	(0.98)
	α	0.25	0.14	0.05	0.05	0.03	0.05	−0.02	0.01	−0.07	−0.06	−0.32
		(5.71)	(3.02)	(1.02)	(1.14)	(0.82)	(0.85)	(−0.41)	(0.13)	(−1.24)	(−1.07)	(−4.16)
NAIC Avg.	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)

Table 7: Performance of Portfolios Sorted on β^{DEF} - 1993-2014

This table presents the results of analyses examining the performance of portfolios formed by sorting on β^{DEF}. For the unconditional portfolio analysis, at the end of each month t, all bonds are sorted into decile portfolios based on an ascending ordering of 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 (β^{DEF} $10-1$). For the conditional portfolio analysis, at the end of each month t, all bonds are sorted into two 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^{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 (β^{DEF} $10-1$) in each NAIC designation group. Finally, for each β^{DEF} decile portfolio as well as the β^{DEF} $10-1$ portfolio, we calculate the average excess return across the two NAIC designation groups, and refer to this as the NAIC Avg. group. The rows labeled β^{DEF}_{Post} and α present the intercept coefficient and slope coefficient on DEF, respectively, from a regression of 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. The rows labeled Excess Return present the time-series average of the monthly excess returns. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero post-formation exposure to default factor risk, a zero mean excess return, and a zero alpha, are shown in parentheses. Excess returns and alphas are in percent per month. The analysis covers portfolio formation (return) months t ($t+1$) from December 1992 (January 1993) to November (December) 2014, inclusive.

	Value	β^{DEF} 1	β^{DEF} 2	β^{DEF} 3	β^{DEF} 4	β^{DEF} 5	β^{DEF} 6	β^{DEF} 7	β^{DEF} 8	β^{DEF} 9	β^{DEF} 10	β^{DEF} $10-1$
Unconditional	β^{DEF}_{Post}	0.68	0.65	0.72	0.72	0.74	0.83	0.82	0.94	1.07	1.34	0.67
		(17.39)	(17.12)	(20.51)	(22.84)	(25.99)	(29.62)	(25.06)	(27.97)	(34.89)	(31.95)	(9.79)
	Excess Return	0.38	0.32	0.29	0.27	0.27	0.30	0.34	0.35	0.42	0.48	0.10
		(5.19)	(4.54)	(4.00)	(3.87)	(4.01)	(4.01)	(4.46)	(4.32)	(4.65)	(4.42)	(1.31)
	α	0.08	0.03	0.00	-0.02	-0.01	-0.00	0.03	0.04	0.04	0.02	-0.06
		(2.10)	(0.88)	(0.01)	(-0.50)	(-0.39)	(-0.16)	(1.08)	(1.21)	(1.25)	(0.53)	(-0.85)
NAIC 1	β^{DEF}_{Post}	0.68	0.69	0.74	0.68	0.75	0.78	0.81	0.91	1.04	1.25	0.57
		(16.60)	(17.18)	(20.18)	(18.74)	(25.77)	(23.49)	(25.12)	(19.53)	(24.73)	(24.04)	(7.57)
	Excess Return	0.36	0.28	0.28	0.26	0.26	0.29	0.31	0.31	0.40	0.43	0.07
		(4.78)	(3.68)	(3.76)	(3.71)	(3.69)	(3.84)	(4.11)	(3.48)	(4.36)	(3.86)	(0.82)
	α	0.07	-0.03	-0.02	-0.01	-0.03	-0.01	0.02	0.00	0.04	-0.01	-0.08
		(1.65)	(-0.71)	(-0.51)	(-0.14)	(-0.99)	(-0.22)	(0.74)	(0.09)	(1.05)	(-0.14)	(-0.97)
NAIC 2	β^{DEF}_{Post}	0.66	0.60	0.72	0.71	0.77	0.80	0.89	1.02	1.15	1.48	0.82
		(12.24)	(13.04)	(17.39)	(16.51)	(20.04)	(21.60)	(22.68)	(23.47)	(26.75)	(30.78)	(10.23)
	Excess Return	0.41	0.35	0.36	0.30	0.34	0.30	0.38	0.43	0.48	0.54	0.12
		(5.24)	(4.78)	(4.90)	(4.09)	(4.68)	(4.16)	(4.80)	(4.77)	(5.01)	(4.67)	(1.36)
	α	0.12	0.07	0.08	0.01	0.05	0.01	0.05	0.08	0.07	0.04	-0.08
		(2.12)	(1.40)	(1.78)	(0.26)	(1.38)	(0.39)	(1.35)	(1.81)	(1.56)	(0.77)	(-0.99)
NAIC Avg.	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)

Table 8: Persistence of Portfolio Performance - 1993-2014

This table presents portfolio alphas calculated from returns in months two through 12 after portfolio formation. At the end of each month t, we form portfolios as described in Tables 4-7. For the portfolios formed by sorting on β^{CBMKT}, β^{TERM}, and β^{DEF}, we examine the unconditional portfolios. 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 three lags and testing the null hypothesis of a zero alpha, are shown in parentheses. Alphas are in percent per month. The analysis covers portfolio formation (return) months t $(t+k)$ from k months prior to January 1993 (January 1993) to k months prior to December 2014 (December 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	0.21	−0.15	−0.36	0.21	−0.15	−0.35	0.05	−0.00	−0.05
	(3.40)	(3.29)	(3.12)	(3.46)	(2.43)	(8.23)	(−3.35)	(−6.35)	(5.81)	(−3.04)	(−5.68)	(1.28)	(−0.03)	(−0.75)
3	0.14	0.16	0.12	0.15	0.09	0.20	−0.13	−0.33	0.20	−0.15	−0.35	0.04	−0.00	−0.04
	(3.22)	(3.15)	(2.84)	(3.25)	(2.02)	(8.24)	(−2.99)	(−5.86)	(5.77)	(−3.08)	(−5.63)	(1.05)	(−0.10)	(−0.66)
4	0.16	0.18	0.14	0.17	0.12	0.19	−0.14	−0.34	0.21	−0.16	−0.37	0.05	−0.00	−0.05
	(4.03)	(3.85)	(3.52)	(4.08)	(2.98)	(8.20)	(−3.25)	(−5.85)	(5.98)	(−3.38)	(−5.86)	(1.44)	(−0.13)	(−0.89)
5	0.15	0.16	0.13	0.16	0.10	0.21	−0.16	−0.37	0.21	−0.15	−0.36	0.06	−0.01	−0.07
	(4.17)	(3.77)	(3.55)	(4.19)	(3.00)	(9.33)	(−3.52)	(−6.57)	(6.40)	(−3.24)	(−5.98)	(1.58)	(−0.28)	(−1.06)
6	0.14	0.14	0.11	0.14	0.08	0.20	−0.13	−0.34	0.20	−0.15	−0.35	0.07	0.01	−0.06
	(3.89)	(3.61)	(2.95)	(3.88)	(2.23)	(8.92)	(−2.98)	(−6.18)	(6.14)	(−3.27)	(−5.79)	(1.94)	(0.20)	(−1.03)
7	0.13	0.14	0.10	0.13	0.06	0.19	−0.14	−0.33	0.20	−0.15	−0.35	0.06	−0.01	−0.07
	(3.84)	(3.56)	(2.75)	(3.78)	(1.78)	(7.83)	(−3.06)	(−5.82)	(6.15)	(−3.31)	(−5.80)	(1.70)	(−0.38)	(−1.23)
8	0.12	0.13	0.10	0.12	0.06	0.20	−0.15	−0.35	0.19	−0.15	−0.33	0.07	−0.01	−0.08
	(3.59)	(3.37)	(2.63)	(3.51)	(1.63)	(8.07)	(−3.24)	(−6.06)	(5.96)	(−3.23)	(−5.61)	(2.09)	(−0.24)	(−1.39)
9	0.12	0.13	0.10	0.12	0.06	0.20	−0.16	−0.36	0.19	−0.15	−0.34	0.09	−0.01	−0.10
	(3.47)	(3.23)	(2.59)	(3.39)	(1.72)	(8.19)	(−3.58)	(−6.38)	(6.14)	(−3.18)	(−5.65)	(2.67)	(−0.29)	(−1.81)
10	0.11	0.12	0.09	0.11	0.06	0.21	−0.14	−0.35	0.18	−0.15	−0.33	0.08	−0.02	−0.10
	(3.41)	(3.22)	(2.53)	(3.35)	(1.73)	(8.78)	(−3.01)	(−5.98)	(5.94)	(−3.25)	(−5.59)	(2.33)	(−0.62)	(−1.85)
11	0.11	0.12	0.09	0.12	0.06	0.20	−0.14	−0.34	0.17	−0.16	−0.33	0.06	−0.01	−0.07
	(3.54)	(3.30)	(2.63)	(3.46)	(1.72)	(8.45)	(−3.11)	(−5.92)	(5.77)	(−3.36)	(−5.57)	(1.71)	(−0.28)	(−1.29)
12	0.11	0.12	0.09	0.11	0.06	0.19	−0.14	−0.33	0.15	−0.14	−0.29	0.05	−0.01	−0.06
	(3.46)	(3.22)	(2.69)	(3.33)	(1.72)	(8.28)	(−2.99)	(−5.86)	(5.06)	(−3.05)	(−5.03)	(1.31)	(−0.35)	(−1.07)

Table 9: Insurer Holdings Regressions - 2003-2014

This table presents the results of WLS regressions of insurer holdings on bond variables using MV as the weight. The dependent variable is $\%InsHeld$, 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 NAIC designation is 2, and 0 otherwise. In columns (1)–(3), we report the time-series averages of coefficients from monthly cross-sectional regressions, t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis that the time-series average of the estimated coefficient is zero, in parentheses, and the average number of monthly observations n. In columns (4)–(6), we report coefficients from panel regressions with year fixed effects, t-statistics that use standard errors clustered by letter rating and time in parentheses, and the number of panel observations n. The analysis covers months t from December 2002 to November 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				Y	Y	Y
n	4539	4539	4539	653591	653591	653591

Table 10: Alphas and Insurer Holdings of Independently Sorted Portfolios - 2003-2014 This table presents the alphas (Panel A) and insurer holdings (Panel B) of portfolios formed by sorting on NIG proximity and term factor exposure. 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. We use the intersections of the 10 β^{TERM} groups and the two rating-based (BBB− and NAIC 2 No BBB−) groups to form 20 portfolios. We then calculate the market value-weighted month $t+1$ excess return of each of the 20 portfolios. Within each β^{TERM} group, we calculate the excess return of the portfolio that is long the BBB− portfolio and short the NAIC 2 No BBB− portfolio ([BBB−]−NAIC 2 No BBB−). Within each NIG proximity group, we calculate the excess return of the portfolio that is long the β^{TERM} 10 portfolio and short the β^{TERM} 1 portfolio (β^{TERM} $10-1$). Finally, for each β^{TERM} group we calculate the average excess return across the two rating-based portfolios, and refer to this as the Avg. portfolio. Also, for each rating-based group, we calculate the average excess return across the 10 β^{TERM} portfolios, and refer to this as the β^{TERM} Avg. portfolio. Panel A presents the monthly alphas (in percent per month) and Panel B presents the time-series average of the monthly portfolio-level $\%InsHeld$ (in percent) for each of these portfolios. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero mean alpha or difference in $\%InsHeld$, are shown in parentheses. The analysis covers portfolio formation (return) months t ($t+1$) from December 2002 (January 2003) to November (December) 2014, inclusive.

Panel A: Portfolio Alphas

	β^{TERM} 1	β^{TERM} 2	β^{TERM} 3	β^{TERM} 4	β^{TERM} 5	β^{TERM} 6	β^{TERM} 7	β^{TERM} 8	β^{TERM} 9	β^{TERM} 10	β^{TERM} Avg.	β^{TERM} $10-1$	
NAIC 2 No BBB−	0.37	0.18	0.04	0.05	−0.00	−0.01	0.05	−0.06	−0.11	−0.16	0.03	−0.53	(−5.24)
BBB−	0.25	0.18	0.16	0.08	0.02	0.08	0.08	0.09	0.04	−0.08	0.09	−0.34	(−2.99)
Avg.	0.31	0.18	0.10	0.06	0.01	0.04	0.06	0.01	−0.04	−0.12	0.06	−0.44	(−5.06)
[BBB−]−NAIC 2 No BBB−	−0.12	0.01	0.12	0.03	0.02	0.09	0.03	0.14	0.15	0.07	0.06		
	(−1.57)	(0.09)	(2.02)	(0.61)	(0.38)	(1.51)	(0.53)	(1.87)	(1.91)	(0.75)	(2.14)		

Panel B: Percent of Portfolio Held By Insurers

	β^{TERM} 1	β^{TERM} 2	β^{TERM} 3	β^{TERM} 4	β^{TERM} 5	β^{TERM} 6	β^{TERM} 7	β^{TERM} 8	β^{TERM} 9	β^{TERM} 10	β^{TERM} Avg.	β^{TERM} $10-1$	
NAIC 2 No BBB−	24.50	27.76	30.64	32.69	38.44	42.10	43.72	44.68	48.35	47.97	38.09	23.47	(26.95)
BBB−	18.97	22.83	23.53	28.55	34.36	37.11	40.92	40.31	44.95	43.74	33.53	24.77	(24.60)
Avg.	21.73	25.30	27.08	30.62	36.40	39.60	42.32	42.50	46.65	45.86	35.81	24.12	(38.66)
[BBB−]−NAIC 2 No BBB−	−5.54	−4.92	−7.12	−4.13	−4.08	−5.00	−2.81	−4.37	−3.40	−4.23	−4.56		
	(−7.78)	(−9.53)	(−10.41)	(−8.96)	(−8.57)	(−11.04)	(−3.52)	(−6.47)	(−4.63)	(−4.46)	(−19.20)		

Table 11: Insurer Holdings and Portfolio Alphas - 2003-2014

This table presents the results from single and Fama and MacBeth (1973, FM) regressions of portfolio alphas on insurer holdings for the 20 β^{TERM} and rating-based portfolios described in Table 10. 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. $\%InsHeld$ is calculated as the proportion of a bond's market value held by life and property/casualty insurers. $\%InsHeld_{Constrained}$ and $\%InsHeld_{Unconstrained}$ are calculated as the proportion of a bond's market value held by constrained and unconstrained, respectively, life and property/casualty insurers. $\%InsHeld_{Constrained,\perp}$ is the component of $\%InsHeld_{Constrained}$ that is orthogonal to $\%InsHeld_{Unconstrained}$, calculated as the intercept plus the residual from a cross-sectional regression of $\%InsHeld_{Constrained}$ on $\%InsHeld_{Unconstrained}$. $\%InsHeld_{Unconstrained,\perp}$ is the component of $\%InsHeld_{Unconstrained}$ that is orthogonal to $\%InsHeld_{Constrained}$, calculated as the intercept plus the residual from a cross-sectional regression of $\%InsHeld_{Unconstrained}$ on $\%InsHeld_{Constrained}$. t-statistics, testing the null hypothesis of a zero coefficient (Single) or zero average coefficient (FM, adjusted following Newey and West (1987) using three lags), are shown in parentheses. The analysis covers portfolio formation (return) months t $(t+1)$ from December 2002 (January 2003) to November (December) 2014, inclusive.

	Single (1)	FM (2)	Single (3)	FM (4)	Single (5)	FM (6)	Single (7)	FM (8)	Single (9)	FM (10)
$\%InsHeld$	−0.012	−0.007								
	(−6.46)	(−3.97)								
$\%InsHeld_{Constrained}$			−0.048	−0.041			−0.073	−0.040		
			(−8.05)	(−4.51)			(−3.37)	(−4.10)		
$\%InsHeld_{Constrained,\perp}$									−0.071	−0.040
									(−3.91)	(−3.86)
$\%InsHeld_{Unconstrained}$					−0.015	−0.007			0.007	0.001
					(−5.89)	(−3.35)			(1.22)	(0.21)
$\%InsHeld_{Unconstrained,\perp}$							0.009	0.002		
							(1.21)	(0.52)		
Intercept	0.476	0.301	0.478	0.284	0.468	0.262	0.708	0.362	−0.215	0.040
	(7.22)	(5.02)	(8.97)	(5.59)	(6.60)	(4.72)	(3.57)	(3.99)	(−1.18)	(0.41)
Adj. R^2	68.22%	8.74%	77.08%	10.24%	63.92%	7.77%	77.64%	14.52%	79.88%	14.52%

Table 12: Portfolio Alphas - 1978-1992 versus 1993-2014

This table presents the alphas of portfolios formed by sorting on NIG proximity or systematic risk exposure for the 1978-1992 and the 1993-2014 periods. At the end of each month t, we form portfolios as described in Tables 4-7. For the portfolios formed by sorting on β^{CBMKT}, β^{TERM}, and β^{DEF}, we examine the unconditional portfolios. 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 January 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 three 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	0.05	0.00	−0.05	0.06	0.01	−0.05	−0.03	0.04	0.07
		(0.15)	(0.14)	(−1.06)	(−0.02)	(−1.32)	(2.01)	(0.05)	(−0.84)	(2.17)	(0.15)	(−0.88)	(−0.67)	(1.17)	(1.03)
1993-2014	α	0.13	0.14	0.12	0.14	0.09	0.23	−0.13	−0.36	0.21	−0.16	−0.37	0.08	0.02	−0.06
		(3.07)	(2.86)	(2.92)	(3.14)	(2.10)	(8.57)	(−3.00)	(−6.14)	(5.91)	(−3.30)	(−5.99)	(2.10)	(0.53)	(−0.85)
1978-2014	α	0.01	0.01	−0.04	−0.00	−0.05	0.05	0.00	−0.05	0.06	0.01	−0.05	−0.03	0.04	0.07
		(0.14)	(0.13)	(−0.88)	(−0.02)	(−1.05)	(1.76)	(0.05)	(−0.75)	(1.54)	(0.12)	(−0.75)	(−0.58)	(0.91)	(0.88)
	α^{1993}	0.13	0.14	0.16	0.14	0.14	0.17	−0.14	−0.31	0.15	−0.16	−0.31	0.11	−0.02	−0.13
		(1.93)	(1.82)	(2.70)	(2.08)	(2.29)	(4.46)	(−2.08)	(−3.55)	(3.11)	(−2.41)	(−3.53)	(1.88)	(−0.33)	(−1.27)