CHAPTER 1

Can a Combination of Treasuries and Equities Replace Credit in a Portfolio?

INTRODUCTION

The corporate bond market is one of the largest markets in the world. According to the Security Industry and Financial Markets Association (SIFMA), $1.38trn worth of new corporate bonds were issued in the United States alone in 2018, while total equity issuance that year was only $0.22trn.[1] Since equity and bonds of the same issuer represent claims to the same underlying operating cash flows and are affected by the same set of firm fundamentals, their valuations are innately related, as formalized in Merton (1974).[2] The economic link between firms' corporate bonds and equity has led some investors to consider the possibility of replacing credit with a simple "barbell" combination of equities and Treasuries that will result in similar returns with the added benefit of higher liquidity. Studies examining this idea offered varying conclusions, partly because of the differences in approach and sample period. Asvanunt and Richardson (2017), for example, argued that corporate bonds carry a positive premium for bearing exposures to default risk using a long time series of corporate bond index returns since 1926 after properly adjusting for the bond exposures to Treasuries. In contrast, Norges Bank (2017) found that in an asset allocation framework, corporate bond indices did not offer any benefit to an equities/Treasuries portfolio in a more recent sample period from 1988 to 2017.

Given the central role played by credit in asset allocation, we conduct a comprehensive two-part study spanning almost three decades and leveraging our unique access to the Bloomberg Barclays Indices pricing and analytics data as well as a proprietary firm-level capital structure mapping developed by Barclays. Similar to most studies, we start with an asset-allocation-level analysis and examine the effect of including an allocation to a broad credit index (consisting of investment-grade [IG] and high-yield [HY] bonds) in various equities/Treasuries portfolios. Although very simple conceptually, great care should be taken in the implementation phase to control for the reallocation effect. This effect is caused by the possible difference between the equities/Treasuries mix in the portfolio and the one implied by the introduction of the allocation to credit. To demonstrate this issue, note that credit returns can be seen as a combination of equities, Treasuries plus some credit-specific returns. If the credit index equivalent mix of equities and Treasuries is different from that of the equities/Treasuries in the benchmark that the credit allocation is added to, the introduction of credit will effectively change the mix of equities and Treasuries in the original benchmark and thus affect performance. For example, in a portfolio with an initial large allocation to equities (relative to Treasuries), adding credit indirectly increases the weight of Treasuries. If Treasuries happened to rally on average during the sample period, adding an allocation to credit is likely to increase the risk-adjusted returns of the portfolio. Interpreting such a result as a confirmation of the benefit provided by credit may be incorrect if the improvement is due mostly to the increased weight of Treasuries in the portfolio rather than to the contribution of the credit-specific component of credit performance. The existence of the reallocation effect explains, at least in part, why different studies came up with opposing conclusions when using different time periods in the analysis.

We explicitly neutralize the reallocation effect in our analysis by finding the equivalent combination of equities and Treasuries that would best mimic the month-to-month return fluctuations of the credit index. The performance improvement from including the equivalent equities/Treasuries combination instead of the credit index captures the reallocation effect. We find that an allocation to credit improved the risk-adjusted performance of the benchmark regardless of the original mix of equities and Treasuries, controlling for the reallocation effect. For the period 1993 to 2019, for example, adding an allocation to a (market capitalization weighted) credit portfolio comprised of IG and HY indices increased the Sharpe ratio of a 60/40 equities/Treasuries portfolio from 0.71 to 0.86.

The latter result is not sufficient, however, to conclude that the barbell approach has no merit because our analysis has not taken into account a second element we term the "mismatch effect." This effect emanates from the differences between commonly used bond and equity indices in terms of issuer composition and sector weights. A nonnegligible number of bond issuers do not have publicly traded equities, especially issuers with ratings below investment grade. Similarly, many small capitalization firms (especially in sectors such as technology) do not have public debt outstanding. Furthermore, even if a company is represented in both indices, the weights (or size relative to other issuers) of its bonds and stock are likely to differ, causing a mismatch at the issuer level and possibly at the sector level as a result of difference in the typical financing channels across industries (i.e., some industries traditionally use more debt or equity to finance their operations). The results of the analysis can therefore be affected when stocks of companies with no corporate bonds earn extreme returns during the sample period or when sectors with a larger representation in the credit indices (relative to the equity indices) perform differently from other sectors.

Isolating the true contribution of credit requires explicitly controlling for the mismatch effect. This, in turn, cannot be done at the aggregate level (i.e., index) and requires an issuer-level analysis that allows a comparison of bonds with a risk-equivalent combination of Treasuries and equity from the same company. To reduce interference from idiosyncratic risk, we aggregate the issuer-level returns to portfolios and compare the performance of the corporate bond portfolio and replicating portfolio with matched issuers, weights, and risk. Since both reallocation and mismatch effects are absent in this case, any return difference between an issuer's corporate bonds and the combination of its risk-matched equity and Treasuries would represent the unique contribution of credit.

After careful issuer and risk matching, we find that corporate bonds achieved better risk-adjusted performance than a combination of Treasuries and equities of the same companies with similar risk exposures, in both IG and HY, regardless of the weighting schemes used. From 1993 to 2019, the corporate bond portfolio outperformed the risk-equivalent combination of Treasury and issuer-matched equity portfolio by more than 1.5%/yr and 3%/yr for IG and HY, respectively. The information ratios of the bond-over-replication portfolio were all relatively large and ranged from 0.47 to 0.84, depending on the portfolio weighting schemes. The results were qualitatively similar across subperiods, ratings, sectors, and geographies.

To make sure our findings do not reflect simply our choice of the risk-matching method, we consider two alternative approaches: matching based on total volatility and using analytical hedge ratios based on the Merton (1974) model. We find that the bond portfolio still delivered outperformance over the replication portfolios and that the bond outperformance was not driven by outliers, underweighting equity risk, or illiquidity. Taken together, the evidence suggests that corporate bonds offered a clear return benefit over a risk-matched combination of equities and Treasuries that was not driven by any specific industry, time period, rating, or our choice of risk matching approach, and could not be explained by risk or liquidity considerations.

What accounts for credit's return advantage over the matched combination of equities and Treasuries? The persistent nature of our results points to the existence of systematic drivers, perhaps certain risk premia or market anomalies that benefit bondholders rather than idiosyncratic and transient effects. To test various possible explanatory variables, we regress the monthly performance of the bond portfolio in excess of the replication portfolio against the returns of a host of commonly used risk factors and market anomalies. The regression results suggest that two in particular are responsible for the majority of credit return outperformance over the replicating portfolio: equity and bond volatility risk premia (VRP) and the low risk anomaly. Investors in corporate bonds earn the equity VRP, since holding a corporate bond is akin to owning a risk-free bond coupled with a short put option on the firm's assets (Merton 1974), which creates a short exposure to the volatility of the firm's underlying assets.[3] The impact of the bond VRP (i.e., exposure to interest rate volatility) is a result of both possible rate convexity mismatch between the bond portfolio and the replicating portfolio of equities and Treasuries, which we did not directly control for, as well as the existence of call provisions.[4] Choi, Mueller, and Vedolin (2017) show that a short rates volatility exposure (via selling delta-hedged calls and puts on Treasury futures) generates on average a positive risk premium (termed the bond variance risk premium). Israelov (2019) finds that corporate bond returns have a significant positive exposure to short interest rate volatilities strategies.

The second driver of corporate bond outperformance over the replicating portfolio is related to a manifestation of the low-volatility phenomenon well documented across asset classes. A substantial body of research documents that in both equities and fixed income markets, less volatile securities earned higher risk-adjusted returns compared with securities that experienced higher volatility (Ambastha, Ben Dor, Dynkin, Hyman, and Konstantinovsky 2008; Chapter 11; Ang, Hodrick, Xing, and Zhang 2006, 2009; Frazzini and Pedersen 2014). The main explanation for this phenomenon is that most investors are leverage-constrained and therefore have a bias toward riskier securities that offer higher absolute returns as they are unable to generate similar returns investing in the lower-risk securities. This dynamic bids up prices for riskier securities and drives down their returns relative to otherwise similar, less risky, securities (Asness, Frazzini, and Pedersen 2012; Frazzini and Pedersen 2014). The evidence we find indicates that this phenomenon is also present across the capital structure of a firm for which bonds and stocks play the role of the low- and high-volatility securities, respectively. In other words, investors who hold a favorable view on a firm have incentive to express it via the firm's stock rather than a leveraged (risk-matched) position in the firm's bonds. As a result, on average, bonds will outperform stocks of the same firms on an ex ante risk-matched basis.

It is important to emphasize that while the VRP premia and the low-volatility factor jointly are able to *explain* most of the corporate bond outperformance, they are not easily accessible directly in practice. Capturing the two VRPs requires trading equity and interest rate derivatives daily, while the equity low-volatility factor requires buying and shorting a large number of individual stocks with leverage. Harvesting the VRPs and equity low-volatility factor is therefore challenging for several reasons. First, capacity constraints in derivatives and stock loan markets limit the ability to implement these strategies on the scale needed in aggregate. For example, given the current size of the US corporate market (as of April 2020, the total market value of the Bloomberg Barclays corporate bond indices [IG and HY] was approximately $7trn), it would take more than a decade to execute trades in the Treasury option market to replicate the interest rate volatility exposure of the corporate bond indices without imposing any significant price impact. Second, most institutional investors face explicit or implicit limitations on their ability to invest in derivative markets or short stocks. Third, transacting on a daily basis in these markets requires different knowledge and infrastructure from that needed to invest in equities, Treasuries, and corporate bonds over longer horizons. Fourth, investors attempting to capture these factors directly would incur significant trading costs. The VRP strategies require daily hedging with futures, and the equity low-volatility factor requires shorting, which imposes additional shorting costs. Our results, however, imply that investors in corporate bonds should take into account the existing exposures embedded in their corporate bond portfolios from a risk management perspective, especially when considering direct allocations to short volatility strategies or equity low-volatility strategies.

Taken together, our results suggest that using a Treasury-equity barbell as a substitute for a credit allocation with the added benefit of higher liquidity is not trivial to implement and requires care to control for the reallocation and mismatch effects. In addition, even with careful implementation, investors will be missing out on important sources of returns and on average will end up underperforming an otherwise similar portfolio with an allocation to credit.

The rest of the chapter is organized as follows. The first section examines the role of credit in an asset allocation framework, while the next section presents an issuer-level analysis. It reviews in detail the construction methodology and performance of the corporate bond portfolio and its risk-matched equity/Treasury replication portfolio. The third section investigates additional alternative risk-matching approaches to understand to what extent our results are sensitive to the exact specification we use. The fourth section investigates various possible drivers that explain the performance difference between the bond and equities/Treasuries portfolios. The last section concludes and outlines some possible directions for future research.

BENEFIT OF CREDIT IN AN ASSET ALLOCATION CONTEXT

To evaluate the effect of adding credit to an equities/Treasuries portfolio, we perform a simple asset allocation exercise, starting with a portfolio composed of equity and Treasury indices, and examine whether increasing the allocation to credit improves the Sharpe ratio of the portfolio. We use the S&P 500 Index (total return including dividends) and the Bloomberg Barclays Treasury index to represent the Equity and Treasury allocations and the combined Bloomberg Barclays IG and HY Corporate Bond Indices (weighted by market value) to capture the performance of credit (based on total returns). The sample spans the period from January 1993 to December 2019.

Figure 1.1 plots the Sharpe ratios of different equities/Treasuries benchmarks (20/80, 40/60, 60/40, and 80/20 equities/Treasuries mixes) as a function of the percentage of credit allocation added. The allocation to credit replaces a mix of equities and Treasuries with the same ratio as in the original benchmarks, respectively. The Sharpe ratios display a hump-shaped pattern as a function of the weight allocated to credit for all benchmark

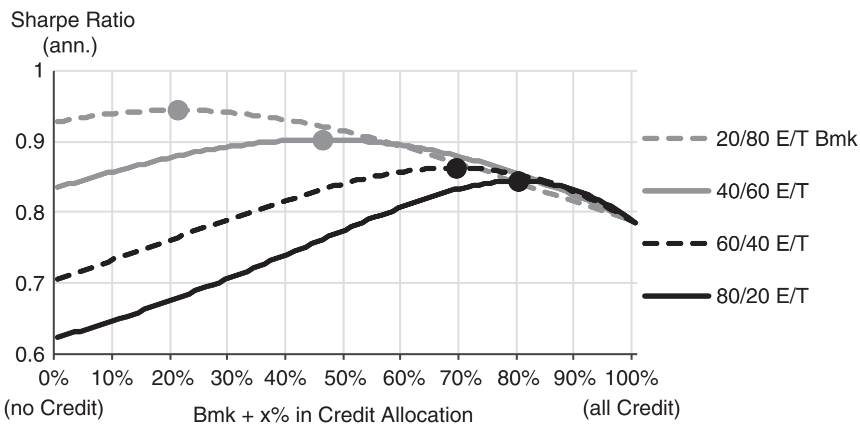

FIGURE 1.1 Sharpe Ratios of Equities/Treasuries Benchmarks with Credit Allocation
Note: The added credit allocation replaces a mix of equities/Treasuries with the same ratio as in the original benchmark.
Source: Bloomberg, Barclays Research

portfolios. The portfolio's Sharpe ratios always increased once some credit was allocated to the original benchmarks; then the ratios reached a maximum and started decreasing. The patterns suggest that having an allocation to credit improves the Sharpe ratio of an equities/Treasuries benchmark regardless of the original mix.

Decomposing the Effects of Including Credit

Does the improvement from credit allocation mean that credit cannot be replaced by a combination of equities and Treasuries? Not necessarily, as there are several effects stemming from the inclusion of credit. Some of them are unique to credit as an asset class, while others can be replicated by equities and Treasuries alone. The first is a reallocation effect, caused by the fact that the inclusion of credit may alter the original equities/Treasuries mix in the new portfolio, given the sensitivity of credit to the Treasury and equity markets. This reallocation effect is illustrated in Figure 1.2. For example, if we start with a 60/40 equities/Treasuries portfolio and replace 40% of it with a credit index, the credit index could be equivalent to, for example, a 20/80 equities/Treasuries mix, and thus the inclusion of credit effectively increases the Treasury weight in the portfolio and will change its performance. Therefore, a positive impact from the reallocation effect does not mean that credit cannot be replaced by equities and Treasuries, because this effect could have been replicated by changing the mix of equities and Treasuries in the original portfolio.

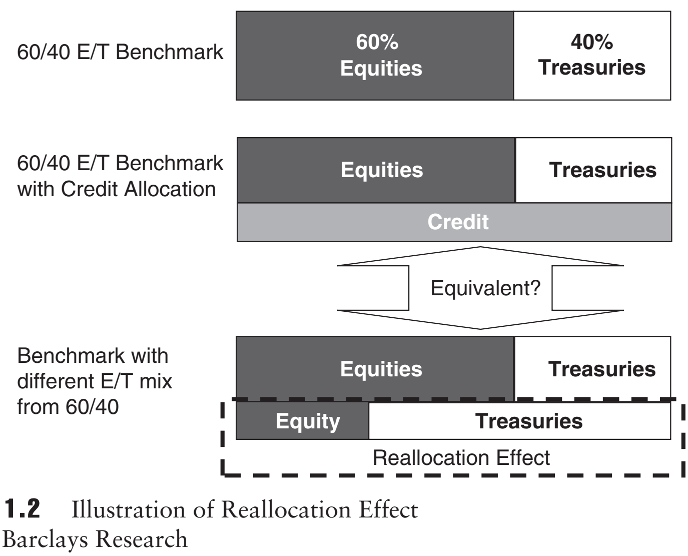

FIGURE 1.2 Illustration of Reallocation Effect
Source: Barclays Research

The second effect stems from issuer and weight mismatch between bond and equity indices. For example, there are a number of private issuers in the HY bond index with no publicly traded equities and, similarly, there are a number of public companies with no outstanding corporate bonds, especially in certain sectors, such as technology. Even if the same company is included in both indices, the weights of the bonds and the stock of the same issuer could be different, which would cause a weight mismatch at the issuer and eventually at the sector level. Figure 1.3 illustrates this by comparing the weights of the information technology and communications sectors in the S&P 500 and Bloomberg Barclays Corporate and High Yield Indices as of the end of December 2019. The weight of the tech sector is seven times as large in the equity index (21%) compared to that in the bond indices (3% each). The pattern is reversed when it comes to the communications sector. The benefit of including the credit index could therefore come from the fact that it had overweighed issuers and sectors that happened to outperform on a relative basis. This mismatch effect cannot be replicated explicitly by investing in equity and Treasury indices, but any benefit resulting from it is likely to be temporary and not structural.

The third contributor is the component of credit return profile that is either a compensation for the risk embedded in corporate bonds due to their specific payment structure or results from some market anomalies. This effect, if it exists, is unique to credit as an asset class and is more likely to persist since it is structural.

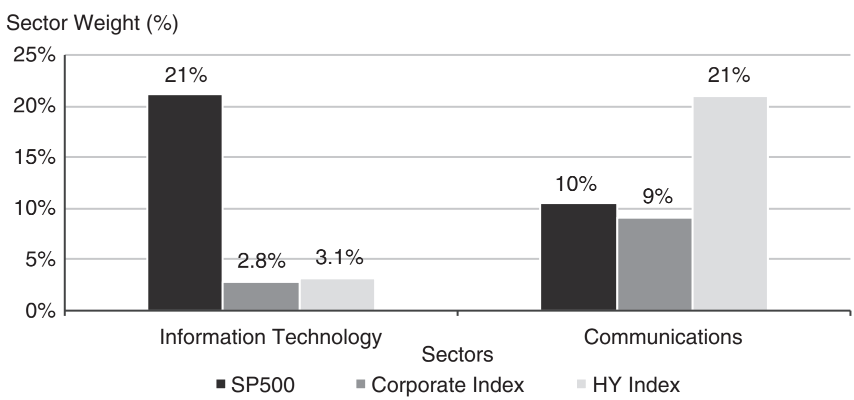

FIGURE 1.3 Sector Weight of Technology and Communications Sectors in Equity and Bond Indices (as of December 2019)
Note: Sector weights are calculated using market value at the end of the month.
Source: Bloomberg, Compustat, Barclays Research

Out of the three effects, the reallocation effect can be mitigated by changing the mix of equity and Treasury indices directly in the original portfolio, whereas the mismatch effect and the unique benefit of credit are specific to the credit index. Therefore, without teasing out the reallocation effect, evaluating the effect of including credit could be misleading. In this section, we decompose the overall effect of including the credit index into the reallocation effect vs. credit index–specific effects, which include the mismatch effect and the unique benefit of credit as an asset class.

To estimate the reallocation effect, we construct a replication portfolio composed of equities (S&P 500), Treasuries (Treasury index), and cash (3m T-bills) that minimizes the monthly return differences (tracking error volatility) relative to the credit index. To determine the weights of equities and Treasuries, we estimate each month a regression of trailing 36m credit returns against the S&P 500 and the Treasury index returns. The coefficients on the S&P 500 and the Treasury index are their respective weights in the replication portfolio in the coming months, and any excess is allocated in T-bills.[5] Figure 1.4 plots the historical weights of equities and Treasuries in the replication portfolio. On average, the replication portfolio allocates 16% to equity, 81% to Treasuries, and 3% to 3m T-bills.

To estimate the reallocation effect associated with an equities/Treasuries benchmark with an x% allocation in credit, we merely need to look at the performance of the same original benchmark with an x% allocation in the replication portfolio. Its performance would capture the reallocation effect. The difference between the benchmark with credit and the benchmark with the replication portfolio would capture any credit-specific effect.

To illustrate how we separate the reallocation and the credit-specific effects, we first start with a 60/40 equities/Treasuries benchmark portfolio and vary the allocation to credit. The x% allocation in credit replaces the

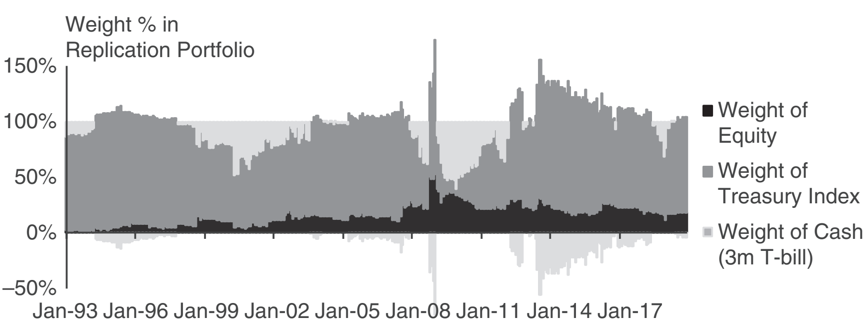

FIGURE 1.4 Historical Weights of Equities/Treasuries in the Replication Portfolio
Source: Bloomberg, Compustat, Barclays Research

original mix of equities/Treasuries (e.g., 0.6*x% equities and 0.4*x% Treasuries in this case). Figure 1.5 plots the portfolio Sharpe ratios when we increase the credit allocation to a 60/40 equities/Treasuries portfolio. The dotted line plots the Sharpe ratio of the benchmark portfolio (no credit), which had a Sharpe ratio of 0.71 from January 1993 to December 2019. The solid line plots the Sharpe ratios with x% in credit, and the distance of the solid line and the dotted line captures the net effect of including credit. The dashed line in the middle plots the Sharpe ratios with x% allocation in the replication portfolio, and the distance between the dashed line and the dotted line captures the reallocation effect. The distance between the solid line and the dashed line then identifies the credit-specific effect. The credit index-specific effect is positive for all allocation levels in credit in this case, achieving the maximum Sharpe ratio of 0.86 with 69% allocation in credit. The overall effect of including credit is also positive for all allocation levels, while the reallocation effect stays positive for most levels.

In reality, the fractions of equity and Treasury allocation in investors' portfolios depend on a number of factors, such as the investors' objectives, risk preferences, historical evaluation periods they use, and strategic outlooks on each asset class. This chapter does not intend to prescribe an

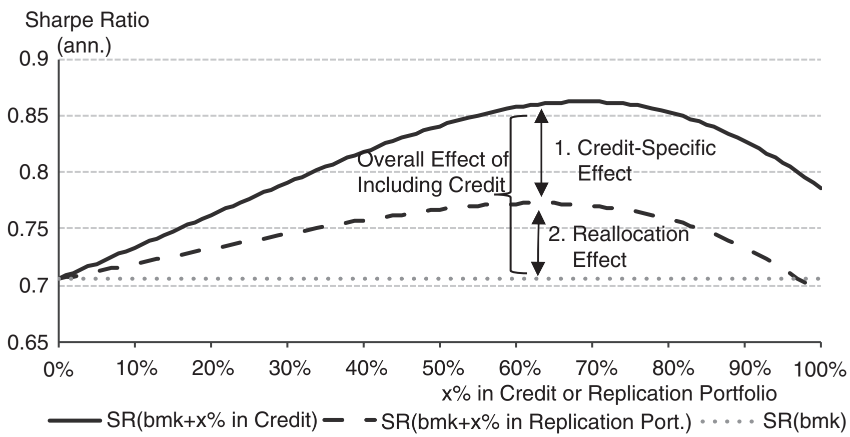

FIGURE 1.5 Performance of 60/40 Equities/Treasuries Portfolio with x% Credit Allocation

Note: The added credit allocation replaces a mix of equities/Treasuries with the same ratio as in the original benchmark. The monthly returns used are from January 1993 to December 2019.

Source: Bloomberg, Compustat, Barclays Research

optimal asset allocation recipe. Our objective is to assess the additive value of credit to an equities/Treasuries portfolio. In order to examine whether the unique benefit of credit is present for a wide range of E/T mixes or is specific to certain E/T allocations only, we repeat the previous analysis for different equities/Treasuries benchmarks. The results are shown in Figure 1.6, with Panel A, B, and C for the 20/80, 40/60, and 80/20 equities/Treasuries benchmarks, respectively. The reallocation effect can be positive or negative depending on the original benchmark. For example, the reallocation effect in Panel C for the 80/20 E/T benchmark is positive. This is because the optimal allocation in this period was 22/78 E/T, and including the credit index effectively increased the allocation in Treasuries, which moved the portfolio closer to the optimal allocation and thus created a positive reallocation effect. Another thing worth noting is that in a simple exercise of adding credit allocation to an equities/Treasuries benchmark, the effect on the Sharpe ratios is sensitive to what asset the credit allocation replaces. For example, when adding the same credit index to a 60/40 equities/Treasuries benchmark, the portfolio Sharpe ratio will increase if credit replaces equities but will decrease if credit replaces Treasuries. This is precisely because of the reallocation effect. When credit replaces equities, it effectively adds more Treasuries to the portfolio and moves the E/T allocation closer to optimal, and vice versa when credit replaces Treasuries. Evaluating the effect of credit without controlling for the reallocation effect could thus be misleading.

In contrast, the credit index-specific effects are positive regardless of the original mix of E/T in the benchmark. We also repeat the analysis using the IG and HY indices separately as the credit portfolio, instead of the IG and HY combined index as in the previous analysis. Overall, we find qualitatively similar results with all the variations.

Next we want to understand how the effects of including credit vary over time, especially during crisis and noncrisis periods. We divided our sample period into crisis periods (the tech bubble: January 2000–December 2002; and the financial crisis: January 2008–December 2009) and noncrisis periods and repeated the analysis for each subperiod. The Sharpe ratios of the 60/40 E/T benchmark with different credit allocations are shown in Figure 1.7, with the results in the crisis and noncrisis periods in Panel A and B, respectively. We find that allocating to credit increased the Sharpe ratios substantially in the two crises (tech bubble and financial crisis) during our sample period, while the benefit of credit was much smaller during the noncrisis months.

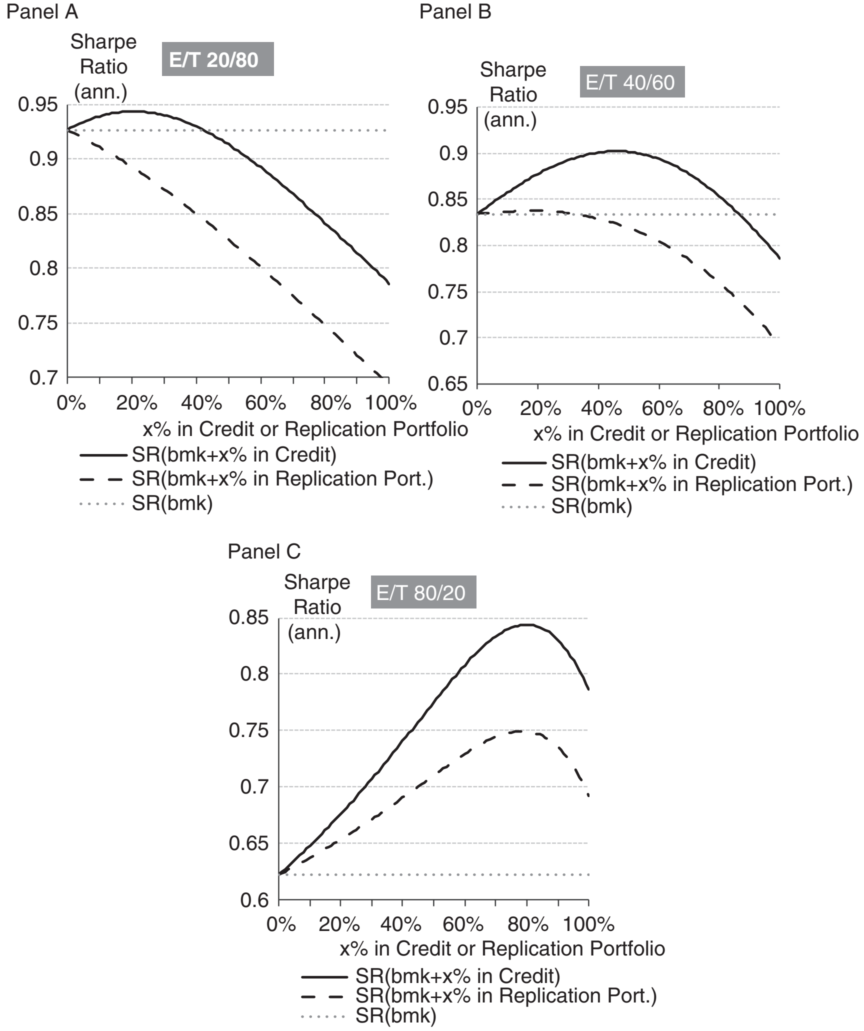

FIGURE 1.6 Sharpe Ratio of Adding x% Credit Allocation to Different Mixes of Equities/Treasuries

Note: The added credit allocation replaces a mix of equities/Treasuries with the same ratio as in the original benchmark. The monthly returns used are from January 1993 to December 2019.

Source: Bloomberg, Compustat, Barclays Research

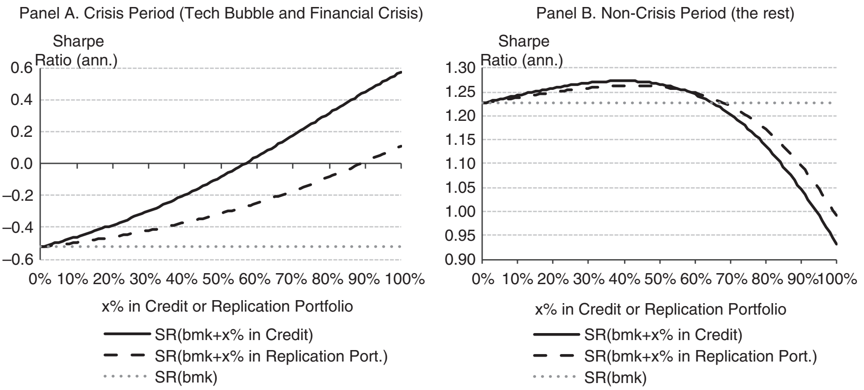

FIGURE 1.7 Sharpe Ratio of Adding x% Credit Allocation to the 60/40 E/T Benchmark in Crisis and Noncrisis Periods
Note: The crisis periods include the tech bubble (January 2000–December 2002) and the financial crisis (January 2008–December 2009). Noncrisis period are the rest of the months in the January 1993–December 2019 period. The added credit allocation replaces a mix of equities/Treasuries with the same ratio as in the original benchmark.
Source: Bloomberg, Compustat, Barclays Research

CAN A CORPORATE BOND BE REPLICATED BY TREASURIES AND SAME-ISSUER EQUITY?

The results in the previous section suggest that credit improves the risk-adjusted performance of an equities/Treasuries benchmark controlling for the reallocation effect irrespective of the original equities/Treasuries mix. Does that mean that credit cannot be replaced by a combination of equities and Treasuries in a portfolio? Not exactly, because there are two components in the credit index–specific effect that we already pointed out: (1) issuer and weight mismatch and (2) the unique benefit of credit as an asset class.

To separate the two effects, we perform an issuer-level comparison of corporate bonds to a combination of the issuer's equity and Treasuries in such a way that it matches the systematic risk exposures of the corporate bonds to make sure that the risk differences in bonds and equities are correctly accounted for. We begin by defining the universe of securities used in the analysis comprising matched bonds and stocks at the company level. We then explain how we construct the bond portfolio and form replication portfolios using Treasuries and equities from the same companies.

Sample Construction and Methodology

The first challenge in our analysis is constructing a company level bonds-to-equities mapping. Bonds and equities have different security identifiers and usually lack a common company identifier. Moreover, companies typically have a single class of common shares traded at any point in time but may have multiple outstanding bonds differing in terms of maturity, seniority, rating, coupon rates, and other structural differences (e.g., callability). A company may also have several different subsidiaries in different industries that issue corporate bonds. Corporate actions often have different effects on outstanding bonds and equities. Bonds issued by the acquired company often continue to trade after the acquisition, while their equities normally cease to do so. The bond-to-equity mapping should also take into consideration the fact that stock and bond identifiers may change over time. We rely on the proprietary mapping algorithm developed by Ben Dor and Xu (2015) to construct the historical matching of corporate bonds to equities.

To create the universe of mapped bonds and equities at the company level, we start with all issuers in the Bloomberg Barclays US Corporate and High Yield indices from January 1990 to December 2019 and link each issuer to equity data from Compustat.[6]

In addition, we have several filters to make sure that bonds and equities in the final sample are tradable. First, we exclude bonds with prices less than $40 because these bonds typically trade on recovery value and have very thin trading. Prices of these bonds may not be representative of actual executable prices.[7] Second, if the mapped equities are ADR, traded OTC or outside of the United States, we remove the company (both equity and bonds) from the universe. This ensures that exchange rate dynamics do not affect stock returns. Third, we remove from the sample penny stocks with beginning-of-month prices less than $1. These stocks usually are thinly traded and could be very volatile.

We perform all analyses separately for IG and HY universes. Conceptually they are all corporate bonds and differ only in rating. In practice, because of restrictions from investment mandates, there is market segmentation between the two markets that results in distinctive market dynamics among the two. For example, see Ambastha, Ben Dor, Dynkin, and Hyman (2010) on the jump in the ratio of a bond's analytical/empirical duration going from Baa (IG) to Ba (HY), and see Chapters 2 to 4 on the forced selling/price pressure when IG bonds get downgraded to HY. To account for the different dynamics in the IG and HY universes, we present all analyses separately for IG and HY in case any result is specific to only one universe. The separate analyses also provide results more relevant to readers interested in only one universe.

TABLE 1.1 Percentage of Bloomberg Barclays US Indices Included in the Sample by Market Value

Year-End Statistics	Corporate Index						High-Yield Index					
	1994	**1999**	**2004**	**2009**	**2013**	**2017**	**1994**	**1999**	**2004**	**2009**	**2013**	**2017**
Index Population ($Billion)	513	900	1,691	2,548	3,703	5,172	133	353	599	704	1,260	1,321
% Mapped	91%	94%	95%	96%	96%	97%	71%	72%	82%	71%	67%	81%
% Included in Final Sample	78%	84%	77%	81%	80%	80%	47%	50%	69%	62%	57%	72%

Note: To calculate the index coverage, we look at the issuer constituents in the return statistics universe at the end of December of the reported years.
Source: Bloomberg, Compustat, Barclays Research

Table 1.1 displays the proportion of Bloomberg Barclays US Corporate and High Yield indices covered by the final sample. The coverage ratio by market capitalization reaches 97% for the IG index and 81% for the HY index at the end of the sample. The coverage ratio is lower for the HY index because a higher percentage of HY issuers are private companies, which do not have publicly traded equities. The difference between the numbers in the rows of "Mapped" and "Included in Final Sample" are due to the three filters we mentioned earlier.

Despite the partial coverage of the two indices, the final sample is very similar to each respective index in terms of key analytics. Figure 1.8 shows that the time series of value-weighted averages of bond-level option-adjusted spreads (OAS) and option-adjusted spread durations (OASD) are very much aligned between the sample and the index. Therefore, any dynamics we observe are unlikely to be driven by the differences between our sample and the indices.

To reduce the effect of idiosyncratic risk, we aggregate issuer-level returns for both corporate bonds and equities to the portfolio level for comparison. In particular, we follow two steps to build a replication portfolio that has the same constituents and issuer weights with systematic risk exposures similar to the bond portfolio. In the first step, we build a bond portfolio and an equity portfolio with the same constituents and the same weight assigned to each issuer's bonds and equity in their respective portfolios to make sure that there is no issuer and weight mismatch. In the second step, we use the equity portfolio together with a Treasury portfolio to construct a replication portfolio that has the same systematic risk exposures as the bond portfolio. The steps are illustrated in Figure 1.9 and discussed in detail next.

Step 1: Constructing Mapped Bond and Equity Portfolios As shown in Panel A of Figure 1.9, each month we construct two portfolios: a bond and an equity portfolio, with identical sets of issuers, and each issuer receiving the same weight in its bonds[8] and its equity, respectively. To allocate the weights among different issuers in the portfolios, we use four intuitive weighting schemes: equal weighting, value weighting using bond market value, equity market value, and total market value (the sum of a company's bond and equity market value), henceforth denoted as EW, Bond-VW , Equity-VW, and Total-VW, respectively. We performed our analysis using all four weighting schemes to ensure that the results were not specific to the choice of weights.

Step 2: Constructing a Replication Portfolio Using Sensitivity Matching Corporate bonds consist of exposures to two key risk factors: a significant Treasury component with exposures to interest rate risk and a credit component driven by firm fundamentals with exposures to market risk that is highly correlated with

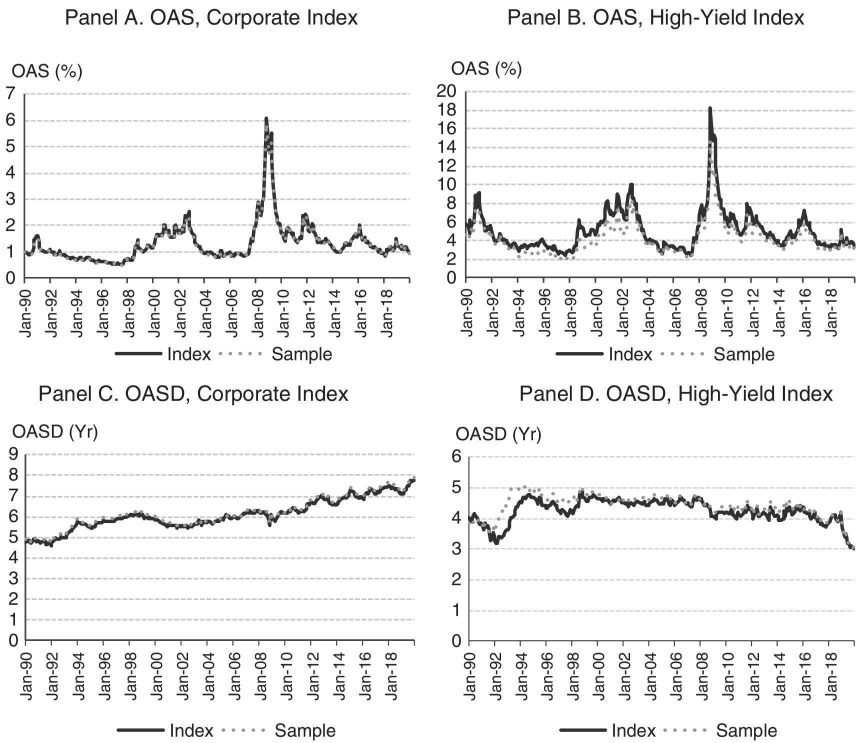

FIGURE 1.8 Characteristics of the Sample vs. Corresponding Indices
Note: OAS and OASD are aggregated bond-level averages weighted by the bond's market value at month-end.
Source: Bloomberg, Compustat, Barclays Research

equities. Equities may have negligible or even negative exposures to interest rate risk and much higher exposure to market risk. Comparing the performance of the bond and equity portfolios directly without any risk matching would yield misleading results. To account for the different risk exposures between bonds and equities, we construct a replication portfolio using a Treasury portfolio and the issuer-matched equity portfolio such that its risk sensitivities match that of the bond portfolio. Panel B of Figure 1.9 illustrates the idea: We vary the weights in the Treasury and the equity portfolios (two unknowns) such that the replication portfolio's sensitivities to the two key risk factors equal that of the bond portfolio (two equations). We solve for the two unknowns in the two equations, and any excess weight (two unknowns may not necessarily add up to 1) is allocated in cash (3m T-bills).

The portfolio weights are calculated monthly in two steps. First, we proxy for the market risk factor using the S&P500 index total returns and the interest rate risk factor using returns of the 10-yr on-the-run (OTR) Treasury portfolio. We also construct the replication portfolio with the Bloomberg Barclays Treasury Index instead of the OTR 10-yr Treasury portfolio. The results are qualitatively similar (included in Appendix 1.1).[9] We estimate the sensitivities (betas) of the bond and equity portfolios to these two factors through monthly ordinary least squares (OLS) regressions with exponential decay weighting using trailing 36m data to avoid any look-ahead bias.[10] In the replication portfolio we use the 10-yr OTR treasury portfolio, which by construction has a beta of 1 to the interest rate risk factor and a beta of zero to the S&P 500 returns. Second, we solve for the weights on the equity portfolio and 10y Treasuries of the replication portfolio (two unknowns) such that its two factor sensitivities match those of the bond portfolio (two equations).[11] Any extra weight is allocated to 3m T-bills.

Table 1.2 reports the average factor sensitivities across all 36m-calibration periods and the percentage of the calibration periods in which the respective sensitivities are statistically significant. Consistent with our expectation of a considerable Treasury component in bond returns, 97% (IG) and 40% (HY) of the time the bond portfolios had statistically significant sensitivities to Treasuries within all trailing 36m calibration windows with an average sensitivity of 0.60 for IG and 0.09 for HY. The bond portfolios also had a credit component with significant sensitivities to the S&P 500 index 72% of the time for the IG index and 85% for the HY index. The equity portfolios had significant sensitivities to the same market factor 100% of the months. On average, the equity portfolio has no sensitivity to Treasury returns for the IG index and negative sensitivity to Treasury returns for HY and is significant only 12% (IG) and 29% (HY) of the time.

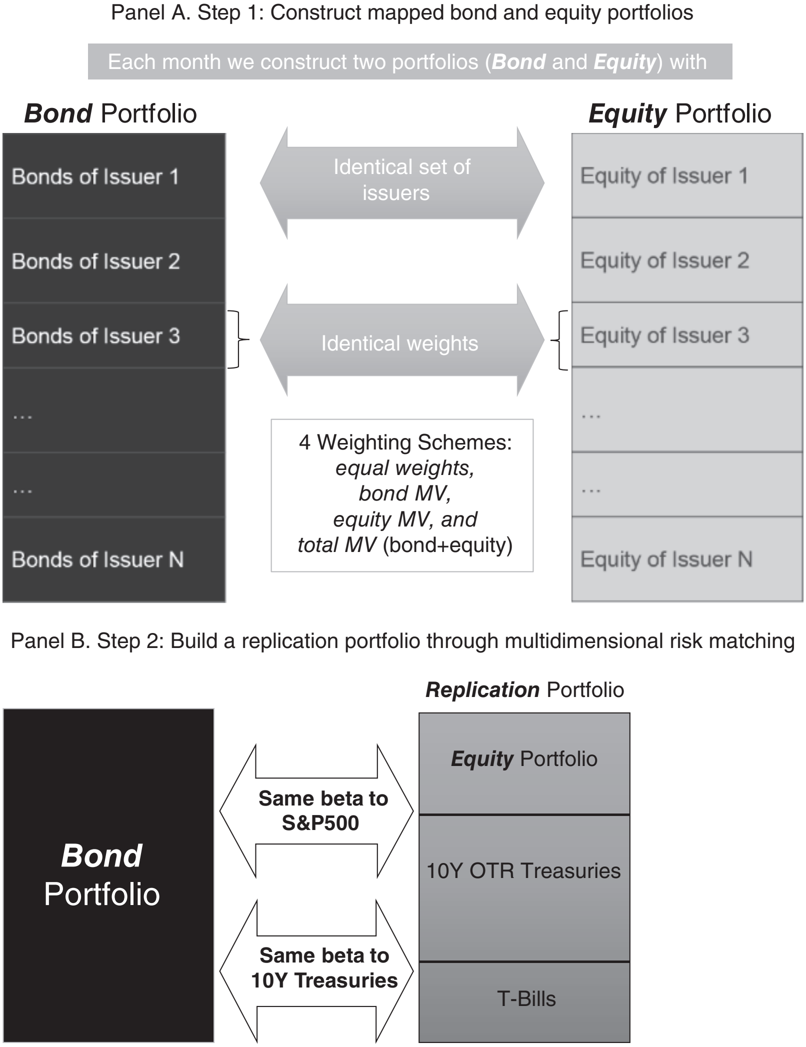

FIGURE 1.9 Illustration of Risk-Matching Steps
Source: Barclays Research

TABLE 1.2 Pre-Formation Average Sensitivities

	Portfolio	$\beta_{S\&P\ 500}$	% of mth w. 5% sig.	$\beta_{10y\ Treasury\ ret.}$	% of mth w. 5%-sig.	Average Adj. R^2
IG	Bond	0.09	72%	0.60	97%	75%
	Equity	0.94	100%	0.00	12%	86%
HY	Bond	0.25	85%	0.09	40%	43%
	Equity	1.28	100%	–0.39	29%	67%

Note: The pre-formation sensitivities each month were estimated from trailing 36m regression and then averaged across the time series from January 1993 to December 2019. All individual issuer returns were equally weighted, and bond total returns were used.
Source: Bloomberg, Compustat, Barclays Research

Figure 1.10 reports the average weights in each asset for the replication portfolio. The replication portfolio in IG has 9% of its weight in equities, 60% in Treasuries, and the rest in cash. The replication portfolio in HY has twice the weight in equities (19%) and much smaller weights in Treasuries (18%), consistent with what we would have expected.

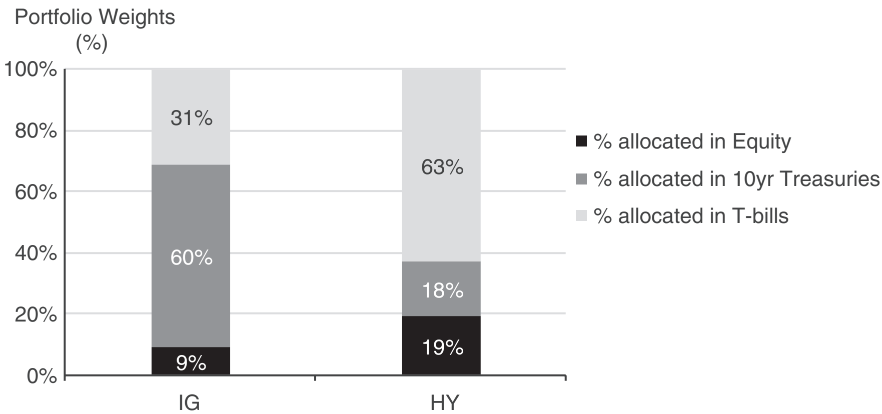

FIGURE 1.10 Average Portfolio Weights
Note: The corresponding weights were estimated from trailing 36m regression and then averaged across the time series from January 1993 to December 2019. All individual issuer returns were equally weighted, and bond total returns were used.
Source: Bloomberg, Compustat, Barclays Research

Did the ex ante factor matching succeed in matching the two sources of risk in the bond portfolio? To examine this question, we look ex post whether the difference portfolio (bond-over-replication portfolio) had any exposures to the equity and Treasury factors. If the risk matching approach did a good job, we would expect the difference portfolio to have no significant exposures to the two factors. Indeed, that is the case. Table 1.3 shows the regression results of the post-formation portfolio returns on the S&P 500 and Treasury return factors. The difference portfolio (bond over replication) had no exposures to both factors with small insignificant beta coefficients in the –0.02 to –0.01 range and still a significant alpha in both IG and HY. The adjusted R^2 for the difference portfolio is very small (–0.2% for IG and –0.5% for HY) compared to that for the bond and the replication portfolio, respectively, which are in the 33 to 84% range. The adjusted R^2s indicate that the bond and replication portfolios themselves have significant exposures to the two factors, but the replication portfolio does a good job replicating the systematic risk of the bond portfolio as the factor exposures have been neutralized in the difference portfolio.

Portfolio-Level Performance

Table 1.4 shows the performance statistics of the bond, the replication, and the bond-over-replication portfolios for the four weighting schemes in both IG and HY. The last column shows the correlation between the bond and the replication portfolios in each weighting scheme for IG and HY,

TABLE 1.3 Post-Formation Portfolio Return Sensitivities

	Portfolio	Intercept	t-stat.	$\beta_{S\&P500}$	t-stat.	$\beta_{10y\ Treasury\ Ret.}$	t-stat.	adj. R^2
IG	**Bond over Replication**	**0.15**	**2.54**	**–0.01**	**–0.44**	**–0.02**	**–0.65**	**–0.2%**
	Bond	0.12	1.90	0.12	4.35	0.56	14.72	61%
	Replication Portfolio	–0.03	–0.87	0.13	8.44	0.59	22.91	84%
HY	**Bond over Replication**	**0.30**	**2.73**	**–0.01**	**–0.25**	**–0.01**	**–0.17**	**–0.5%**
	Bond	0.26	2.27	0.28	5.42	0.03	0.41	33%
	Replication Portfolio	–0.03	–0.53	0.29	11.31	0.04	0.89	55%

Note: The post-formation portfolio returns are from January 1993 to December 2019.
Source: Bloomberg, Compustat, Barclays Research

TABLE 1.4 Performance of Bond-over-Replication Portfolios

	Portfolio	Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
IG	Bond	EW	6.48	5.02	0.81	–8.22	–13.80	
		Bond-VW	6.20	5.18	0.73	–6.84	–14.23	
		Equity-VW	6.37	5.04	0.79	–6.54	–11.61	
		Total-VW	6.35	5.05	0.78	–6.42	–11.99	
	Replication Portfolio	EW	4.85	4.55	0.54	–5.81	–9.04	0.82
		Bond-VW	4.64	4.78	0.47	–8.53	–15.93	0.78
		Equity-VW	4.81	4.70	0.51	–6.93	–10.07	0.85
		Total-VW	4.78	4.71	0.51	–7.26	–10.58	0.84
	Bond over Replication	**EW**	**1.63**	**2.93**	**0.56**	**–3.11**	**–13.52**	
		Bond-VW	**1.56**	**3.35**	**0.47**	**–5.67**	**–9.61**	
		Equity-VW	**1.56**	**2.70**	**0.58**	**–3.59**	**–8.11**	
		Total-VW	**1.57**	**2.79**	**0.56**	**–3.90**	**–8.10**	

(Continued)

TABLE 1.4 *(Continued)*

Portfolio		Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
HY	Bond	EW	7.99	6.71	0.83	–15.58	–25.13	
		Bond-VW	7.62	6.59	0.79	–13.51	–24.80	
		Equity-VW	8.03	5.55	1.01	–13.36	–19.98	
		Total-VW	7.95	5.83	0.95	–13.40	–21.28	
	Replication Portfolio	EW	4.56	5.48	0.40	–8.94	–22.69	0.68
		Bond-VW	5.20	5.49	0.51	–10.42	–22.06	0.72
		Equity-VW	4.68	4.32	0.53	–8.47	–16.79	0.70
		Total-VW	4.88	4.62	0.54	–9.01	–17.96	0.71
	Bond over Replication	**EW**	**3.43**	**5.04**	**0.68**	**–6.64**	**–17.10**	
		Bond-VW	**2.42**	**4.65**	**0.52**	**–4.50**	**–13.52**	
		Equity-VW	**3.34**	**3.97**	**0.84**	**–4.90**	**–8.20**	
		Total-VW	**3.07**	**4.10**	**0.75**	**–4.40**	**–9.41**	

Note: The post-formation portfolio returns are from January 1993 to December 2019.
Source: Bloomberg, Compustat, Barclays Research

respectively. The numbers suggest that the replication portfolios have high correlations with the bond portfolios, around 0.80 for IG and 0.70 for HY. The high correlations are consistent with the results in Table 1.3 that the replication portfolios successfully mimicked the factor exposures of the bond portfolios post-formulation. Despite the similarity in risk between the two portfolios, the bond portfolios produced much higher average returns than the replication portfolios, regardless of the weighting schemes and in both IG and HY. The bond portfolios outperformed the otherwise similar replication portfolios by over 1.5%/yr in IG and around 3%/yr in HY. The bond portfolios also had better risk-adjusted performance in terms of higher Sharpe ratios than the replication portfolios in both IG and HY. The information ratios of bond-over-replication portfolios ranged from 0.47 to 0.84 across different weighting schemes.

Moreover, the bond outperformance was not limited to a single period. Figure 1.11 Panel A compares the Sharpe ratios of bond vs. the replication portfolios in five-year subperiods for both IG and HY. The bond portfolios had higher Sharpe ratios than the replication portfolios in most subperiods except 1998 to 2002 for HY. The subperiod performance comparison was similar in all weighting schemes. Moreover, Panel B of Figure 1.11 shows more detailed time-series dynamics of the bond outperformance by plotting the cumulative returns and information ratios of the bond-over-replication portfolios in trailing windows (12m for cumulative returns and 36m for information ratios) over the sample period. The bond portfolio outperformed the replication portfolios in most periods, but in some periods, the replication portfolio did outperform bonds.

Performance Dynamics in Subsamples and European Markets

We also examine the consistency of bond outperformance, both in and out of sample. Within the original US sample, we find that the bond-over-replication outperformance was consistent across ratings and GICS sectors. Many anomalies with significant in-sample results became insignificant after their initial publication. (See, e.g., Linnainmaa and Roberts 2018.) For this reason, out-of-sample performance is often viewed as strong validation of any in-sample findings. As out-of-sample test, we evaluate whether the bond outperformance is present in the European markets. We find that in European markets, bond portfolios also had higher average returns and Sharpe ratios than the equity-treasury-replication portfolios constructed using the same risk-matching approach. The information ratios of bond over replication portfolios are about 0.4 for IG and 0.67 for HY. All detailed results are included in Appendix 1.2.

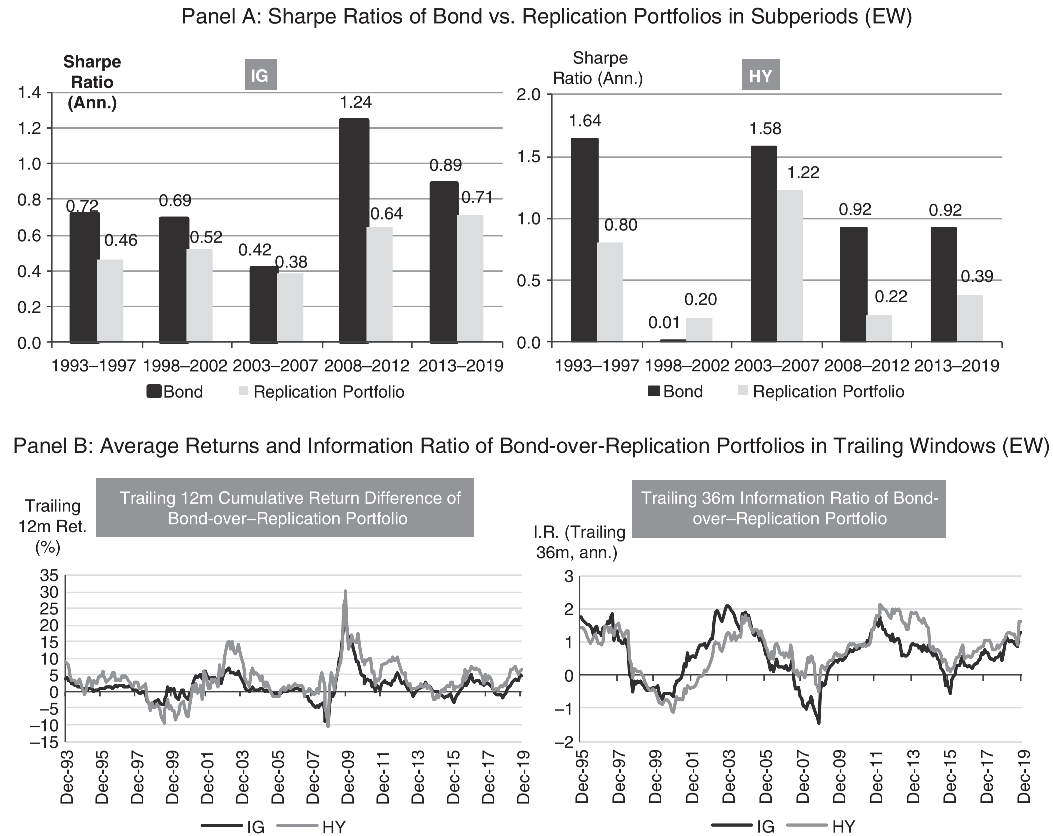

FIGURE 1.11

Note: The post-formation portfolio returns are from January 1993 to December 2019. Portfolio returns are formed from equal-weighting issuer returns.

Source: Bloomberg, Compustat, Barclays Research

Overall, we find that across subperiods, subsamples, and geographies, corporate bonds offer greater return benefit than a portfolio of Treasuries and equities with similar systematic risk. The additional return benefit that corporate bonds offer suggests that they cannot be replaced by a combination of Treasuries and equities.

RISK MATCHING USING ALTERNATIVE APPROACHES

Risk matching is one key element in creating a good replication portfolio for the bond portfolio in order to make a fair comparison of performance. In practice, investors may have different views on which risk exposures are the most important for them besides the factor risk sensitivities we used for risk matching (sensitivity matching). In this section, we consider two alternative approaches of risk matching. The first is simple and intuitive: matching by total volatility of the bond and the equity portfolio. Total volatility captures both systematic risk and idiosyncratic risk of a portfolio altogether and might be an important concern for some investors. We also need to bear in mind that total volatility captures only one aspect of risk and might not be sufficient for a good replication. The second approach we consider is using the analytical hedge ratios implied by the Merton (1974) model for the credit component of bonds and the analytical durations for the Treasury component. The analytical hedge ratios are appealing since they take into consideration an individual company's characteristics, have theoretical underpinning, and may be more forward looking than the hedge ratios calculated from trailing regressions. However, their actual hedging ability could be sensitive to the assumptions made in the theoretical models.

Risk Matching Using Total Volatility

For each bond portfolio, we construct a replication portfolio using its respective equity portfolio and cash. To make the volatility of the replication portfolio match that of the bond portfolios, we scale the equity portfolios by relative historical portfolio-level volatility of bond to equity and allocate the rest of the portfolio in 3m T-bills (cash).[12] Each month, the volatilities of bond and equity portfolios are calculated from respective portfolio returns in the trailing 36m window. The results using alternative window length are similar. The scaled equity portfolio with cash is denoted as volatility-matched replication portfolio.

Table 1.5 shows the performance statistics of the bond, the volatility-matched replication, and the bond-over-replication portfolios, as well as the correlations between the bond portfolio and the volatility-matched

TABLE 1.5 Bond vs. Volatility-Matched Equity/Treasury Portfolio Performance

Portfolio		Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
IG	Bond	EW	6.48	5.02	0.81	–8.22	–13.80	
		Bond-VW	6.20	5.18	0.73	–6.84	–14.23	
		Equity-VW	6.37	5.04	0.79	–6.54	–11.61	
		Total-VW	6.35	5.05	0.78	–6.42	–11.99	
	Volatility-Matched Replication Portfolio	EW	6.25	5.30	0.73	–6.52	–21.56	0.26
		Bond-VW	5.66	5.69	0.58	–7.50	–30.62	0.26
		Equity-VW	5.90	5.39	0.66	–6.71	–23.51	0.18
		Total-VW	5.86	5.45	0.64	–6.87	–24.80	0.20
	Bond over Replication	EW	0.24	6.30	0.04	–5.01	–33.19	
		Bond-VW	0.53	6.64	0.08	–5.68	–31.86	
		Equity-VW	0.47	6.68	0.07	–4.94	–34.45	
		Total-VW	0.50	6.67	0.07	–4.91	–34.16	

(Continued)

TABLE 1.5 *(Continued)*

Portfolio		Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
HY	Bond	EW	7.99	6.71	0.83	–15.58	–25.13	
		Bond-VW	7.62	6.59	0.79	–13.51	–24.80	
		Equity-VW	8.03	5.55	1.01	–13.36	–19.98	
		Total-VW	7.95	5.83	0.95	–13.40	–21.28	
	Volatility-Matched Replication Portfolio	EW	5.06	7.06	0.38	–8.87	–29.50	0.69
		Bond-VW	5.42	7.04	0.43	–9.88	–28.76	0.65
		Equity-VW	4.95	5.69	0.45	–7.66	–25.26	0.57
		Total-VW	5.14	6.07	0.45	–8.33	–26.11	0.60
	Bond over Replication	EW	2.93	5.45	0.54	–6.71	–15.38	
		Bond-VW	2.21	5.72	0.39	–7.66	–18.97	
		Equity-VW	3.08	5.24	0.59	–5.70	–14.84	
		Total-VW	2.82	5.32	0.53	–5.25	–16.04	

Note: The sample period is from January 1993 to December 2019.
Source: Bloomberg, Compustat, Barclays Research

replication portfolio for each weighting scheme in both IG and HY. In IG, total volatilities were matched well ex post, but the correlations between the bond and replication portfolios were low (around 0.22), suggesting that risk was matched inappropriately using the volatility-matching method. This is because IG bonds have a significant Treasury risk exposure, which is not included in equity volatilities. When risk was matched properly, as in the case of sensitivity matching, the correlations were much higher at around 0.80. Because of the inappropriate risk mismatch between the bond and the replication portfolio in IG, their performance may not be directly comparable.

In HY, the volatility-matched replication portfolios did a decent job in mimicking risk of the bond portfolio. First, the correlations between the bond and the volatility-matched replication portfolios were fairly high at around 0.63, only slightly lower than the correlations using sensitivity matching (around 0.70). Second, the ex-post portfolio volatilities of the bond and the volatility-matched replication portfolios were very similar, as shown in Table 1.5. Moreover, the time-series of trailing 36m vol. of the bond and the volatility-matched replication portfolios were similar at each point in time throughout the sample (not reported for brevity). With similar volatilities, the HY bond portfolios still had higher average returns than the volatility-matched replication portfolios, regardless of the weighting scheme. Moreover, the HY bond portfolios had higher Sharpe ratios than the volatility-matched replication portfolios. The information ratios of bond-over-volatility-matched-replication portfolios ranged from 0.39 to 0.59 across different weighting schemes. The volatility-matching results were very similar in European markets as well.

Analytical Risk Matching Using Hedge Ratios

One drawback of both sensitivity- and volatility-matching methods that we looked at is that they are inherently backward looking, as the weights are calculated from trailing statistics. In reality, the weights might be time-varying and very dynamic. Another approach is to use analytical hedge ratios based on the characteristics of each individual issuer. For the credit component of each bond issuer in our portfolio, we use the analytical hedge ratios implied by the Merton model (1974) to determine the weights on equity. For the Treasury component of each bond issuer, we use the ratio of analytical duration of the issuer's bonds (value-weighted average at the issuer level) to the analytical duration of the OTR 10y Treasury portfolio as the weights on Treasuries. Any excess weight is allocated in T-bills.

Research has shown that analytical equity hedge ratios based on the Merton model make reasonably accurate predictions of how corporate bond returns vary given the corresponding equity returns (Schaefer and Strebulaev 2008). Based on Merton, a corporate bond (D) is short a put on the underlying asset (V) plus a risk-free asset, while the equity (E) is equivalent to a call option on V. Overall, V=D+E. The hedge ratio (change in bond return with respect to change in equity return) can thus be derived analytically.[13]

Table 1.6 shows the distribution of the equity hedge ratios implied by the Merton model by rating. As the rating worsens, the average hedge ratio increases, which is what we would expect for two reasons. First, bonds with lower ratings are closer to default, and their stock valuations are also driven more by the downside as with the bonds. Second, for bonds with lower ratings, the credit component plays a bigger role in their returns than the Treasury component. In addition, the averages were higher than the median in all ratings, suggesting that the equity hedge ratios had some large positive outliers. However, when we compare the average analytical hedge ratios to the empirical hedge ratios calculated using sensitivity matching (last column of Panel A), the analytical hedge ratios were lower by about 5% in both IG and HY.

As the first quartile and five-percentile cut-offs indicate (4.36% and 0.25%, respectively), some HY companies had low hedge ratios, lower than one would expect for a typical HY company. A closer look at the data reveals that some of these firms are internet companies, such as Netflix, which have low levels of debt but also low profitability. Because of their low profitability, they were rated HY initially. Their equity market value may be high, based on expectations of future revenues. High equity market value, together with low debt levels, leads to low leverage ratios. In the Merton model, low leverage ratios are translated into low hedge ratios. As a result, we observe the conceptual inconsistency of HY companies with low hedge ratios. These observations highlight one limitation of the Merton model: Essentially, it uses the leverage ratio as one of the few inputs to determine a firm's hedge ratio and ignores other important aspects of a firm's operations, such as cash flows and profitability. The sensitivity matching method, which relies on past data to extract the empirical hedge ratios, has the advantage of being model free and takes into consideration all aspects of a firm's operations that affected its asset value.

To examine whether the bond outperformance still exists using the analytical hedge ratios, we construct a replication combination for each company using its analytical hedge ratios and then aggregate the company-level replicated returns into a portfolio using the four weighting schemes discussed earlier. Table 1.7 reports the performance of the replication portfolios using analytical hedge ratios and compares it with those using OLS-based empirical hedge ratios (last two columns). Similar to using empirical hedge

TABLE 1.6 Summary Statistics of Merton Hedge Ratios by Rating

Rating	Mean	Median	Std.	Q1	Q3	5 %tile	95 %tile	Avg. Empirical HR (EW) from Sensitivity Matching
All	7.89%	3.39%	10.64%	0.25%	12.66%	0.00%	27.37%	
Aaa/Aa	1.67%	0.03%	4.12%	0.00%	0.93%	0.00%	10.25%	
A	2.80%	0.49%	4.70%	0.01%	3.50%	0.00%	13.44%	
Baa	4.83%	1.55%	6.93%	0.12%	7.08%	0.00%	19.47%	
Ba	8.92%	6.19%	9.37%	1.59%	14.02%	0.04%	25.87%	
B	15.61%	14.49%	12.08%	6.76%	21.89%	0.85%	34.24%	
Caa and below	26.66%	23.83%	17.06%	16.85%	32.10%	6.48%	55.07%	
IG	3.90%	0.90%	6.17%	0.04%	5.27%	0.00%	17.12%	9.28%
HY	14.28%	12.29%	12.92%	4.36%	20.93%	0.25%	34.78%	19.49%

Note: The sample period is from January 1993 to December 2019.
Source: Bloomberg, Compustat, OptionMetrics, Barclays Research

TABLE 1.7 Portfolio Performance and Risk Sensitivities using Analytical vs. Empirical (OLS-Based) Hedge Ratios

Panel A. Portfolio Performance using Analytical vs. Empirical (OLS-Based) Hedge Ratios						
			Using Analytical Hedge Ratios (Merton Model)		Using Empirical Hedge Ratios (OLS Based)	
		Bond Portfolio	Replication Portfolio	Bond over Replication	Replication Portfolio	Bond over Replication
IG	Avg. Ret. (%/yr)	6.59	5.17	1.42	4.96	1.64
	Volatility (%/yr)	5.06	5.43	3.44	4.52	2.93
	Sharpe (Inf.) Ratio (Ann.)	0.82	0.51	0.41	0.57	0.56
	Corr. w. Bond Portfolio Ret.	1.00	0.79		0.82	
	Avg. Weights in Equities		4%		9%	
	Avg. Weights in 10Y Treasury		78%		60%	

(Continued)

TABLE 1.7 *(Continued)*

Panel A. Portfolio Performance using Analytical vs. Empirical (OLS-Based) Hedge Ratios

			Using Analytical Hedge Ratios (Merton Model)		Using Empirical Hedge Ratios (OLS Based)	
		Bond Portfolio	Replication Portfolio	Bond over Replication	Replication Portfolio	Bond over Replication
HY	Avg. Ret. (%/yr)	8.03	5.90	2.12	4.92	3.11
	Volatility (%/yr)	6.83	6.21	5.81	5.72	5.14
	Sharpe (Inf.) Ratio (Ann.)	0.82	0.56	0.37	0.44	0.60
	Corr. w. Bond Portfolio Ret.	1.00	0.61		0.68	
	Avg. Weights in Equities		15%		19%	
	Avg. Weights in 10Y Treasury		52%		18%	

Panel B. Portfolio Ex Post Factor Exposures using Analytical vs. Empirical (OLS-Based) Hedge Ratios

	Dependent Variables: Bond-over-Replication Portfolio Ret.	Intercept	Beta on S&P500	Beta on 10Y Treasury	Adj. R^2
IG	Using analytical hedge ratios	1.673**	0.042	–0.199***	21.7%
	Using empirical hedge ratios (OLS)	1.761**	–0.009	–0.017	–0.3%
HY	Using analytical hedge ratios	3.457***	–0.01	–0.428***	25.9%
	Using empirical hedge ratios (OLS)	3.413**	–0.02	–0.047	0.0%

Note: ***/**/* indicate significance at the 1%/5%/10% levels. The portfolio returns are from January 1993 to December 2019. All Issuers are equally weighted in the portfolios. The analytical hedge ratios use the Merton (1974) implied hedge ratios for equities and the ratio of bond analytical duration to the 10yr Treasury analytical duration as the hedge ratio for Treasuries. The empirical hedge ratios use the hedge ratios that match the 2-factor (S&P 500 and 10yr Treasury) sensitivities of the bond portfolio where the sensitivities are calculated from trailing 36m regressions.

Source: Bloomberg, Compustat, OptionMetrics, Barclays Research ratios, the bond portfolios had higher average returns and Sharpe ratios than the replication portfolios using analytical hedge ratios in both investment grade and high yield. The bond-over-replication portfolios had information ratios of 0.41 in IG and 0.37 in HY with EW. The bond outperformance was similar across weighting schemes.

Another interesting observation is that the correlations between the bond and the replication portfolios were slightly lower when using analytical hedge ratios than when using empirical hedge ratios (0.79 vs. 0.82 in IG and 0.61 vs. 0.68 in HY). The lower correlations suggest that the analytical hedge ratios were less effective at replicating the bond portfolios compared to the empirical ones. To understand why, we regress the bond-over-replication portfolio returns using each type of hedge ratios on the market (S&P 500) and 10y Treasury return factors. The results are shown in Panel B of Table 1.7. The regression results show that the bond-over-replication portfolios using analytical hedge ratios had significantly negative exposures to the Treasury factor, which suggests that the analytical hedge ratios overweight Treasuries. This is to be expected, as prior research shows that the empirical durations (the realized sensitivity of bonds to Treasury returns) of corporate bonds are lower than their analytical durations, especially true in HY and to a less extent in IG (Ambastha et al. 2010). This explanation is also consistent with our findings that the bond-over-replication portfolio in HY had a more negative Treasury exposure than that in IG.[14]

Overall, we find that corporate bonds still offered additional return benefit over a combination of Treasuries and equities constructed using alternative risk matching approaches that properly replicate the bond portfolios. This evidence suggests that corporate bonds cannot be replaced by a combination of Treasuries and equities, regardless of the risk-matching methods.

DRIVERS OF CREDIT NONREPLICABLE RETURNS COMPONENT

In this section, we investigate potential drivers of the return differences between the bond portfolios and their replication portfolios. We examine a number of possible explanations for bond outperformance, such as (1) outliers, (2) underweighted equity risk in the replication, (3) higher bond performance as a compensation for low liquidity, (4) the backward-looking trailing window we used in sensitivity matching is insufficient to capture the time-varying sensitivities between bonds and equities, and (5) the higher Sharpe ratio in bonds is due to their serial correlation in returns. We perform empirical tests to evaluate these possible explanations, and the results ruled out all of the above explanations. The test details and results are included in Appendix 1.3.

Next, we investigate whether the bond outperformance can be explained by risk factors or known risk premia. Besides the Treasury return factor and a host of commonly used equity risk factors (Fama–French five factors on market, size, value, investment, and profitability; momentum), we also include three other factors that can potentially explain the bond outperformance. The first two stem from the nonlinear payoff features in corporate bonds, and the third comes from the low-volatility phenomenon across the capital structure. We first discuss the economic intuition of why these factors might be related to the bond outperformance. Then, to verify whether these factors can indeed explain the bond outperformance, we regress the monthly bond-over-replication returns on these three factors while controlling for a host of other commonly used risk factors.

Risk Factor 1: Equity Variance Risk Premium

In the Merton model (1974), a corporate bond is a short put on the underlying asset plus a risk-free asset, while the company's stock is a call option on the underlying asset. The short put on the underlying asset also can be decomposed into a stock (call) plus a short straddle (a call and put at-the-money (ATM)) position on the underlying asset. Therefore, holding a corporate bond creates the similar exposure to holding a risk-free bond, the stock of the same company, as well as shorting a straddle on the same underlying asset. In our earlier analysis, we accounted for the stock and the risk-free bond (Treasury) in the replication portfolio but did not account for the short straddle exposure that corporate bonds offer. Shorting a straddle is essentially selling volatility, and previous research shows that selling volatility on equities generates a positive premium, termed the equity variance risk premium (VRP). The equity VRP is positive because the option implied volatility is consistently higher than realized volatility (Bakshi and Kapadia 2003; Carr and Wu 2009), so selling equity volatility generates a premium on average. A corporate bond has a short straddle position on the underlying asset, which is essentially a short position on the asset volatility. This short straddle position could have payoffs similar to a short position on the equity volatility, since equity volatility makes up a substantial component of asset volatility of the same company. As shorting equity volatility carries a positive premium (equity VRP), it is possible that the bond outperformance over the replication portfolio is simply capturing the equity VRP. Previous research has also found evidence that credit returns benefit from the equity VRP (Israelov 2019). In our later regression test, the equity VRP is proxied using the returns of shorting a 1m expiry ATM straddle (call + put) on the

SPX (hold to maturity) and daily delta hedged with SPX futures[15] to take out return variations due to the market's directional movements.

Risk Factor 2: Bond Variance Risk Premium

A second source of nonlinearity in corporate bond payoffs is the callable features common in bonds. A considerable fraction of corporate bonds have callable features that allow issuers to repurchase the bonds at a preset redemption price. For issuers, the call feature offers them the option to benefit from declining interest rates (similar to the payoffs of a put on Treasury futures). For bondholders, the embedded call feature is equivalent to selling a put on interest rate futures. Similar to equity VRPs, research has also documented a positive VRP on Treasury rates; that is, the option-implied volatilities are often higher than realized volatilities for Treasury rates, and an investor can collect a positive premium by selling hedged calls and puts on Treasury futures (Choi, Mueller, and Vedolin 2017). Since the call features on the corporate bonds give their holders an embedded short position on interest rate options, part of the bond outperformance may come from the premium of selling volatility on interest rates. Because bond issuers are more likely to call their bonds when interest rates are low, bond returns should be more sensitive to downward volatility than upward volatility. In this case, a short position on Treasury puts should better capture bondholders' exposures instead of a short position on a straddle (a call and a put) in the equity case.

Another source of exposures to interest rate volatility is convexity mismatch. When we constructed the replication portfolios, we carefully matched the sensitivity to interest rates to that of the bond portfolios. However, we did not match convexity of the bond and the replication portfolio. The convexity mismatch between the two could lead to exposure to interest rate volatility.

To test whether either type of exposure is actually the case, we proxy for the call feature premium and convexity exposure using the hold-to-maturity returns of shorting 1m expiry ATM puts and calls separately on the US 10y Treasury futures and daily delta hedged with 10y Treasury futures.[16] The reason that we use puts and calls separately on Treasury futures instead of straddles (a put plus a call combined) in the usual case of proxying for a bond VRP (Israelov 2019) is to distinguish between the call feature premium and the convexity mismatch. With the former, since corporate bonds usually are called when interest rates fall and their market prices are above their predetermined call prices, the payoffs to the embedded call features are equivalent to holding a put option on the Treasury futures for the issuers (shorting a put for the bondholder). Thus, we expect the bond returns to be more sensitive to a short position on an ATM Treasury put than a Treasury call. With the convexity mismatch, bond returns could have exposures to both a call and a put on Treasury futures.

Risk Factor 3: Low-Volatility Phenomenon across the Capital Structure

The low-volatility (low vol.) phenomenon—the tendency of lower-risk stocks to outperform high-risk stocks on a risk-adjusted basis—is widely documented (Ang et al. 2006, 2009; Frazzini and Pedersen 2014). A similar pattern was also detected within credit: Short-maturity bonds had better risk-adjusted and even non-risk-adjusted performance than long-maturity bonds (Ambastha et al. 2008, Chapter 11). One underlying theory behind the low-volatility phenomena is that investors with leverage constraints chase risky assets as a form of taking on leverage and, thus, bid up the prices and drive down the expected returns of risky assets (Asness et al. 2012; Frazzini and Pedersen 2014). As a result, holders of low-volatility assets receive a premium paid by the other leverage-averse investors.

Could the bond outperformance over the replication portfolio made of equities and Treasuries be a manifestation of the low-volatility phenomenon across asset classes? Bonds and stocks represent two extremes of a company's capital structure, with different claims to the same fundamental cash flows of the firm. Bonds are the low-volatility assets, while stocks are the high-volatility assets. According to the low-volatility hypothesis, bonds as the low-volatility assets should have better risk-adjusted performance than stocks, which is consistent with our findings.

In our regression test, we proxy for the low-volatility phenomenon using the BAB (betting-against-beta) factor,[17] which was proposed by Frazzini and Pedersen (2014). This factor longs low-beta stocks and shorts high-beta stocks. It also leverages up the low-beta leg to make the strategy market neutral. This strategy, as it longs the low-volatility stocks and shorts the high-volatility stocks, is designed to capture the time dynamics of the low-volatility phenomenon across equities. The low-volatility dynamics are time-varying because the underlying elements that make investors favor risky over low-volatility assets, such as investor risk aversion and investors' financing constraints, are time-varying. These same underlying dynamics are likely to drive both the within-equity and the cross-capital-structure low-volatility phenomenon. Therefore, the BAB factor, even constructed from equities, might be able to capture, at least partially, the time dynamics of the cross-capital-structure low-volatility phenomenon.

Empirical Tests on Risk Factors

To verify whether these factors can indeed explain the bond outperformance, we regress the monthly bond-over-replication returns on these three factors while controlling for a host of other commonly used factors. If these factors can explain the bond outperformance, the intercept of the regressions should disappear after we include them.

We start with a baseline model that includes two main risk factors that we used earlier: S&P 500 and Treasury (OTR 10y) excess returns over the risk-free rate (3m T-bill). The first (IG) and sixth (HY) columns of Table 1.8 show the regression results for the baseline model using the S&P 500 and Treasury factors (Specification 1). The coefficients are consistent with earlier results. The bond-over-replication portfolio returns had no significant exposures to either factor, indicating that the sensitivity-based risk-matching did a good job neutralizing the bond portfolio's exposures to the two factors in the replication portfolio. The intercept terms were 1.806%/yr for IG and 3.495%/yr for HY, and both were statistically significant, suggesting that the bond portfolios delivered significant outperformance over the replication portfolio when we controlled for any residual S&P 500 and Treasury risk. The adjusted R^2s for the baseline regressions were small at 0.2% for IG and –0.5% for HY, indicating that the majority of the time variation of bond-over-replication portfolio performance cannot be explained by the baseline factors.

As an additional control, we add the commonly used equity risk factors (Specification 2): the Fama–French five (FF5) factors [market (S&P 500 over rf, already in baseline model), value (HML), size (SMB), investment (CMA), and profitability (RMW)] and the momentum (MMT) factor. The market, size, and value factors have been staples of modern asset pricing models used in the literature since Fama and French (1993). The momentum factor has also been used extensively for many years (Jegadeesh 1990; Jegadeesh and Titman 1993). The investment and profitability factors are proxies for the quality factors and have been proposed more recently (Fama and French 2015).The intercepts were still statistically significant after including the commonly used equity factors, which indicates that the bond portfolios still significantly outperformed the replication portfolios after controlling for these common equity risk factors. All together, the Fama–French five factors and momentum factor increased the adjusted R^2 by around 4–5% to 5.71% in IG and 3.57% in HY.

Next, we add the Equity VRP factor (Specification 3) to the host of the control factors. Consistent with our hypothesis, the coefficient on the equity VRP was positive and significant, suggesting that exposures to the equity VRP might be one of the drivers of the bond-over-replication return

TABLE 1.8 Regression Coefficients of Bond-over-Replication Portfolio Monthly Returns on Common Factors

	IG					HY				
Specification	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Variables	**Baseline**	**+ FF5 + MMT**	**+Equity VRP**	**+Bond VRP**	**+BAB (Low-Volatility Factor)**	**Baseline**	**+ FF5 + MMT**	**+Equity VRP**	**+Bond VRP**	**+BAB (Low-Volatility Factor)**
Intercept (%/yr)	1.806**	2.145***	1.673**	1.12	0.801	3.495**	4.153***	3.404***	2.557*	2.108
S&P 500 over rf	–0.013	–0.021	–0.02	–0.027	–0.025	–0.015	–0.032	–0.031	–0.042	–0.039
Treasury over rf	–0.037	–0.032	–0.024	–0.025	–0.014	–0.026	–0.046	–0.034	–0.036	–0.02
SMB (size)		0.01	0.011	0.017	0.016		–0.039	–0.038	–0.029	–0.03
HML (value)		–0.053	–0.052	–0.034	–0.035		–0.081	–0.079	–0.053	–0.055
RMW (profitability)		–0.014	–0.015	–0.022	–0.021		–0.014	–0.016	–0.029	–0.027
CMA (investment)		–0.006	–0.006	–0.027	–0.024		–0.052	–0.052	–0.084	–0.08
MMT (momentum)		–0.029**	–0.029**	–0.037**	–0.037**		–0.018	–0.018	–0.029	–0.029
Equity VRP			0.224**	0.196**	0.148**			0.355***	0.312**	0.244**

(Continued)

TABLE 1.8 (*Continued*)

	IG					HY				
Specification	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Bond VRP (puts)				1.502***	1.368***				2.121***	1.933**
Bond VRP (calls)				–0.046	–0.179				0.106	–0.081
BAB (low vol.)					0.107***					0.151***
adj. R^2	0.15%	5.71%	10.66%	16.14%	29.02%	-0.47%	3.57%	7.85%	12.05%	20.76%
Δ in adj. R^2 from previous model		6%	5%	5%	13%		4%	4%	4%	9%
Δ in Intercept from previous model (%/yr)		0.34	–0.47	–0.55	–0.32		0.66	–0.75	–0.85	–0.45

Note: */**/*** indicates 10%/5%/1%level of significance. The portfolio returns are from January 1996 to December 2019 due to availability of equity option data.
Source: AQR, Bloomberg, CME, Compustat, Ken French data library, OptionMetrics, Barclays Research

difference. Including the equity VRP in the regressions also decreased the intercepts by 47bp in IG and 75bp in HY. Overall, adding the equity VRP increased the adjusted R^2 by 4 to 5% in both IG and HY.

In Specification 4, we add the Bond VRP puts and calls factors to the list of factors in the prior step (including Equity VRP). The coefficients were significant on the Bond VRP puts, but not on the calls, indicating that collecting the call feature premium may be a major contributor to the bond outperformance, while the convexity mismatch may play only a small role. The coefficients on Treasury puts in HY (2.121) were 1.4 times the size of the coefficient in IG (1.502), suggesting that HY bonds benefited more from selling puts on Treasury rates, which is to be expected since there are a higher fraction of callable bonds in HY than in IG. Overall, adding the bond VRP factors decreased the intercepts by 55bp in IG and 85bp in HY and increased the adjusted R^2 by 5% in IG and 4% in HY.

The last regressions (Specification 5) add the BAB factor, which proxies for the low-volatility phenomenon. The coefficients on the BAB factor were positive and significant in both IG and HY, suggesting that the time variation of bond outperformance over the replication portfolio had significant exposures to the low-volatility dynamics in equity. Adding the BAB (low-volatility) factor decreased the intercept by another 32bp in IG and 45bp in HY and increased the adjusted R^2 by 13% in IG and 9% in HY. It is quite a surprising finding that a cross-asset class return difference (bonds over equities and Treasuries) was significantly related to a purely within-equity dynamic. The common return dynamics are driven by investor preferences for riskier assets with higher returns, both across and within asset classes. When macroeconomic conditions change over time, such as when leverage is more stringent, or investor risk aversion is low, investors' preferences for risky assets may become stronger, leading to bigger bond outperformance and bigger equity low-volatility effect at the same time.

The final intercepts after controlling for Treasury risk, the commonly used equity risk factors, equity VRP, bond VRP, and the low-volatility factor were 80bp in IG and 211bp in HY, not statistically significant. In the end, the nonlinear payoff features (equity and bond VRP) and the equity low-volatility effect jointly explained the bond outperformance. It is important to note that these results do not mean that, in practice, corporate bonds are redundant and that an investor can replicate the returns of corporate bonds by selling equity and interest rate volatilities and investing in the equity low-volatility factor together with equities and Treasuries. Harvesting the VRPs and equity low-volatility factor is challenging for several reasons.

First, from an equilibrium perspective, the corporate bond market may be too large for investors to replicate its volatility exposures using derivatives. To illustrate the relative size, we took a snapshot on May 4, 2020: The

Bloomberg Barclays Investment Grade and High Yield Corporate indices have a total market value of more than $7trn, as reported in Table 1.9. In contrast, the SPX options and the 10yr Treasury options have a total open interest of about $4,463bn and $329bn in terms of notional, about 62% and 4% of the market value of the corporate indices. Aside from the size, the liquidity in the options markets may also be limited to support large trades that replicate the existing volatility exposures in the entire corporate bond markets. Daily trading volumes of the SPX and 10yr Treasury options are shown in the second row of Table 1.9. To obtain a rough estimate of the dollar amount of the corporate bonds whose volatility exposures the option strategies are able to replicate subject to their current liquidity, we assume that up to 5% of the daily trading volumes can be allocated to the replication trades without causing any negative price impact. We also assume that the corporate bond's average exposures to short-volatility strategies are roughly 0.196 for equity and 1.65 for interest rates based on regression coefficients in Table 1.8.[18] Given current daily volumes, in one day we would be able to replicate the volatility exposures of $35bn and $1bn of corporate bonds with SPX and Treasury options, respectively, representing only 0.48% and 0.02%, respectively, of the total bond market value.[19] To replicate the overall volatility exposures in the bond indices, it would take 208 trading days (nine months) and 5,273 trading days (21 years) in the SPX and Treasury option markets, respectively, to implement the trades with current liquidity. In reality, the replicating trades collectively can be more than 5% of daily volume, but the negative price impact that they might cause could also wipe out the profit of the trades. Overall, the numbers suggest that the option markets might have limited capacity to absorb trades that replicate the exposures in corporate bonds on a large scale.

Second, selling equity and interest rate volatilities requires trading options and futures, which is not allowed in a lot of traditional type of mandates. Capturing the equity low-volatility factor requires shorting stocks, which is also prohibited in many mandates, such as for mutual funds and pension funds. Moreover, all the returns in the regression including returns for the bond portfolios and the risk factors are gross of transaction costs. In reality, trading the BAB factor requires buying and selling a good number of small-cap stocks on a monthly basis, where the transaction costs could potentially be high on top of the shorting costs. Capturing the VRPs requires daily delta hedging using SPX or Treasury futures, which could also be costly. In contrast, the bond portfolio is fairly inexpensive to trade as its average holding period is four to six years per bond. Another aspect to

TABLE 1.9 Size of Corporate Bonds vs. Option Markets

		Corporate Bond Index	SPX Options	10yr Treasury Options
Total Market Value ($bn)		$7,323	$4,563	$329
Daily Volume (in notional, $bn)			$276	$92
Corporate bond positions that can be replicated in 1 day in each derivative market with 5% DV trading limit	Market value ($bn)		$35	$1
	% total bond market value		0.48%	0.02%
# days to replicate entire corporate market			208	5273

Note: The data was taken as a snapshot at the market close of May 4, 2020. The market value reported for SPX options and 10yr Treasury options (June expiry) are the notional for each contract multiplied by the total open interest of contracts for each type of security. For details of calculation, see notes 18 and 19.
Source: Bloomberg, OptionMetrics, CME, Barclays Research

consider is that the dynamics of volatilities are very different from traditional asset returns in bonds and equities. Therefore, trading volatilities would require building one or more teams with special expertise, and additional infrastructure may be needed for daily trading.

Overall, the equity and bond VRPs, as well as the equity low-volatility factor, help us understand the source of the bond outperformance over equities and Treasuries. Given the limited capacity of derivatives markets, mandate constraints, and explicit and implicit trading costs, it might be difficult for investors to capture the VRPs and the equity low-volatility strategy directly. Corporate bonds, however, provide a single instrument to gain exposures to a variety of risk premia without the need of frequent rebalancing at little additional cost. These findings have important implications for investors seeking exposures in the volatility and equity low-volatility strategies: Existing corporate bondholders should be aware of their effective exposures from their bond portfolios, and nonbondholders should consider buying corporate bonds as an alternative to gain such exposures.

CONCLUSION

We conduct a comprehensive two-part study spanning almost three decades and leveraging our unique access to the Bloomberg Barclays Indices pricing and analytics data as well as a proprietary firm-level capital structure mapping to examine a key fundamental question for any investor who has or considers having an allocation to credit: Can it be replaced in a portfolio by a combination of equities and Treasuries?

We explicitly address two major pitfalls related to the reallocation and mismatch effects, which led to contradictory results in previous studies, and find that introducing an allocation to credit improves the risk-adjusted performance of a host of equities/Treasuries portfolios. At an issuer level, corporate bonds achieved better risk-adjusted performance than a combination of Treasuries and equities of the same companies with similar systematic exposures, in both IG and HY, regardless of the weighting scheme used. Such outperformance was persistent in subperiods, ratings, industries, in both the United States and European markets, and using alternative risk-matching approaches.

Our cross-sectional results suggest that for a majority of issuers, on average, their bonds outperformed their stocks on a risk-adjusted basis, but there were still a nonnegligible proportion of issuers with stocks outperforming their bonds. Based on these results, an interesting future area of research may be to understand what characteristics make it more likely for a company to have bonds that outperform their stocks after adjusting for risk, and vice versa. Portfolio managers with the flexibility of combining corporate bonds and equities in their portfolio could benefit from this line of research by adding another source of alpha to their portfolios.

The nonreplicable component of corporate bond performance was largely explained by credit having exposure to equity and bond VRPs because of the options embodied in corporate bond payoffs and the low-volatility phenomenon across the capital structure where corporate bonds represent the low-risk asset compared to equities. Various constraints facing investors, however, prevent them from realistically replacing credit with a proper combination of Treasuries and equities with an overlay of these strategies. Thus, credit offers an efficient channel to gain exposures to these risk premia.

Even if the ability to replicate credit returns improves because of increased liquidity and capacity in derivatives markets, for example, we would expect from an equilibrium standpoint a repricing in credit such that it continues to offer a unique benefit to investors. From a supply-side perspective (i.e., corporations), issuing corporate bonds is an important financing channel that offers several benefits compared to equity issuance, such as preferential tax treatment. Given the strong demand for bond financing, corporations have incentives to lower bond prices to make spreads attractively high for investors. Given the strong benefits that corporations enjoy from issuing corporate bonds, supply and demand will ensure that corporate bonds will not be replaceable by a combination of equities and Treasuries or by other instruments.

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APPENDIX 1.1

Using Treasury Index as the Treasury Portfolio

When we use the Bloomberg Barclays Treasury Index as both the Treasury Portfolio and the Treasury risk factor, the performance of the replication portfolio increased slightly, as shown in Table 1.10, because the Treasury Index had better performance to duration ratio than the 10yr Treasury Portfolio. However, the qualitative results remain the same as the bond portfolio still outperformed the replication portfolio with higher average returns and higher Sharpe ratios. Notice that the magnitude of the bond-over-replication outperformance decreased in both IG and HY, but the decrease was much smaller in HY because Treasury returns make up a much smaller component for HY bonds.

TABLE 1.10 Performance Statistics of Bond vs. Replication Portfolio (Using Treasury Index)

	Portfolio	Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
IG	Bond	EW	6.48	5.02	0.81	–8.22	–13.80	
		Bond-VW	6.20	5.18	0.73	–6.84	–14.23	
		Equity-VW	6.37	5.04	0.79	–6.54	–11.61	
		Total-VW	6.35	5.05	0.78	–6.42	–11.99	
	Replication Portfolio	EW	5.53	4.59	0.68	–6.10	–9.44	0.82
		Bond-VW	5.34	4.84	0.61	–9.22	–17.21	0.77
		Equity-VW	5.54	4.73	0.67	–7.57	–10.57	0.84
		Total-VW	5.51	4.74	0.66	–7.91	–11.09	0.83
	Bond over Replication	EW	0.95	2.93	0.33	–3.34	–14.72	
		Bond-VW	0.85	3.43	0.25	–5.87	–11.87	
		Equity-VW	0.83	2.74	0.30	–3.85	–10.11	
		Total-VW	0.84	2.85	0.30	–4.15	–10.13	

(Continued)

TABLE 1.10 *(Continued)*

	Portfolio	Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
HY	Bond	EW	7.99	6.71	0.83	–15.58	–25.13	
		Bond-VW	7.62	6.59	0.79	–13.51	–24.80	
		Equity-VW	8.03	5.55	1.01	–13.36	–19.98	
		Total-VW	7.95	5.83	0.95	–13.40	–21.28	
	Replication Portfolio	EW	4.69	5.48	0.42	–8.93	–23.35	0.67
		Bond-VW	5.63	5.54	0.58	–10.39	–22.09	0.72
		Equity-VW	5.07	4.38	0.61	–8.51	–17.69	0.70
		Total-VW	5.27	4.67	0.62	–9.04	–18.53	0.72
	Bond over Replication	EW	3.30	5.06	0.65	–6.65	–17.02	
		Bond-VW	2.00	4.61	0.43	–4.29	–15.28	
		Equity-VW	2.96	3.98	0.74	–4.85	–9.70	
		Total-VW	2.68	4.09	0.65	–4.37	–11.00	

Source: Bloomberg, Compustat, Barclays Research

APPENDIX 1.2

Bond Outperformance in Subsamples

This section examines the consistency of bond outperformance, both in sample and out of sample. Within the original US sample, we examine the bond outperformance by rating and by industry. Many anomalies with significant in-sample results became insignificant after their initial publication (e.g., Linnainmaa and Roberts 2018). For this reason, out-of-sample performance is often viewed as strong validation of any in-sample findings. As an out-of-sample test, we evaluate whether the bond outperformance is present in the European markets.

By Rating

Figure 1.12 compares the annualized Sharpe ratios of the bond with the replication portfolio and shows the information ratio of the bond-over-replication portfolio for each rating. In all rating categories, the bond portfolios have higher Sharpe ratios than their replication portfolios. The returns difference of the bond-over-replication portfolios also have positive information ratio ranging from 0.50 to 0.73. The results hold regardless of weighting schemes.

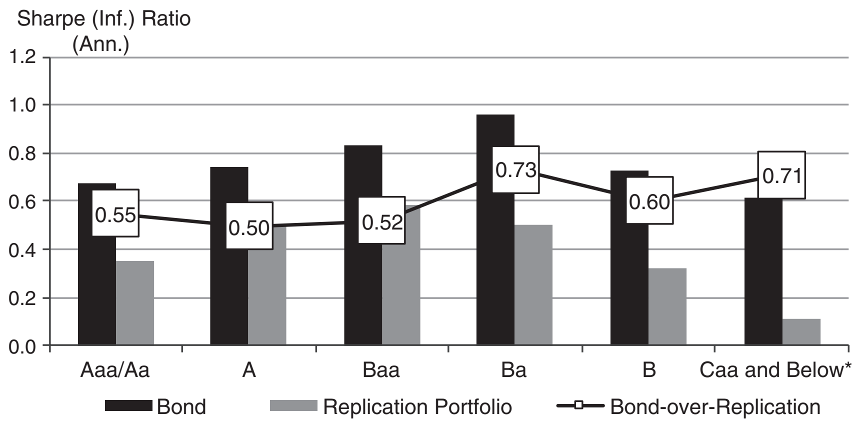

FIGURE 1.12 Sharpe (Information) Ratios of Bond vs. Replication Portfolios by Rating
* The statistics shown for Caa and below are from January 2002 to December 2019 due to lack of observation in this rating bucket from 1993 to 2001.
Note: The portfolio returns are from January 1993 to December 2019. All portfolios are equally weighted.
Source: Bloomberg, Compustat, Barclays Research

By Industry

Figure 1.13 shows the information ratio of the bond-over-replication portfolios by industry (GICS 2-digit sector) for equally weighted portfolios. The results for other weighting schemes are similar and omitted for brevity. In all industries, the bond portfolios outperform the respective replication portfolios in both IG and HY, generating positive information ratios in all sectors, and the results are similar regardless of weighting scheme. The results indicate that the bond outperformance we observed is present in all industries and not driven by a small number of industries.

In European Markets

Is the bond over equity outperformance we found in fact a persistent phenomenon across asset classes, or is it spurious and only a product of data mining? One way to answer this question is to perform the same analysis on a different sample to see if the results hold. Similar to the United States, we construct a sample of mapped bonds and equities at the company level for bonds in the Bloomberg Barclays Pan Euro Corporate and HY indices.[20] Panel A of Table 1.11 reports the percentage of bond market value of the

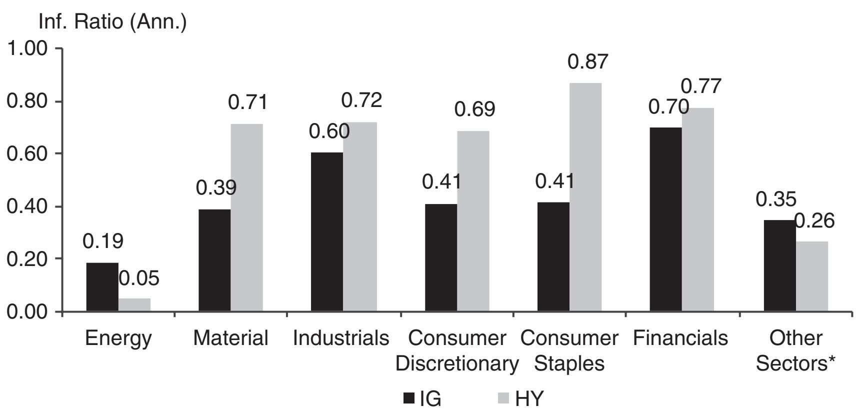

FIGURE 1.13 Annualized Information Ratio of Bond-over-Replication Portfolios by Industry

Note: The portfolio returns are from January 1993 to December 2019. All portfolios are equally weighted. Industries are classified using GICS 2-digit sector. "Other sectors" include utilities, health care, information technology, and telecommunications. These sectors did not have enough observations on their own, so they were grouped together.

Source: Bloomberg, Compustat, Barclays Research

TABLE 1.11 Mapping Coverage and Portfolio Performance in European Markets

Panel A. Mapping Coverage Ratio of Pan Euro Corporate and High-Yield Index Constituents to Compustat (by Bond Market Value)

Year-End Market Value	Pan Euro (€bn) 2003	2007	2011	2014	2017
Corporate Index	1,003	1,205	1,607	1,930	2,330
Mapped	77%	90%	86%	87%	88%
HY Index	67	77	154	348	330
Mapped	56%	67%	66%	74%	73%
Agg. Universe (IG+HY)	1,065	1,282	1,761	2,279	2,660
Mapped	76%	89%	84%	85%	86%

(Continued)

TABLE 1.11 (*Continued*)

Panel B. Bond vs. Replication Portfolio Performance in European Markets

	Portfolio	Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. w. bond portfolio
IG	Bond	EW	3.75	3.42	0.77	–3.87	–8.23	
		Bond-VW	3.67	3.52	0.74	–4.74	–7.14	
		Equity-VW	3.87	3.17	0.88	–3.07	–5.17	
		Total-VW	3.85	3.19	0.87	–3.20	–5.32	
	Replication Portfolio	EW	2.87	2.60	0.69	–2.29	–5.00	0.68
		Bond-VW	2.77	2.82	0.60	–2.79	–6.74	0.65
		Equity-VW	2.79	2.48	0.70	–2.06	–3.46	0.69
		Total-VW	2.81	2.50	0.70	–2.08	–3.72	0.68
	Bond over Replication	EW	0.88	2.51	0.35	–3.25	–8.68	
		Bond-VW	0.91	2.73	0.33	–4.52	–6.68	
		Equity-VW	1.07	2.32	0.46	–3.13	–5.52	
		Total-VW	1.04	2.35	0.44	–3.24	–5.54	

(Continued)

TABLE 1.11 *(Continued)*

Panel B. Bond vs. Replication Portfolio Performance in European Markets

	Portfolio	Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. w. bond portfolio
HY	Bond	EW	6.85	7.96	0.72	–15.45	–31.11	
		Bond-VW	6.30	7.42	0.70	–13.22	–26.96	
		Equity-VW	6.55	7.47	0.73	–14.46	–26.86	
		Total-VW	6.50	7.43	0.73	–14.33	–26.78	
	Replication Portfolio	EW	2.44	6.62	0.21	–8.29	–29.79	0.61
		Bond-VW	2.12	6.93	0.16	–8.39	–29.70	0.58
		Equity-VW	2.20	5.60	0.21	–6.40	–23.39	0.58
		Total-VW	2.23	5.79	0.21	–6.51	–24.10	0.58
	Bond over Replication	EW	4.41	6.54	0.67	–8.93	–14.83	
		Bond-VW	4.18	6.59	0.63	–6.88	–13.21	
		Equity-VW	4.34	6.24	0.70	–8.62	–13.82	
		Total-VW	4.27	6.21	0.69	–8.25	–13.44	

Note: The portfolio returns include the period May 2005 to December 2019.
Source: Bloomberg, Compustat, Barclays Research

bond indices that was successfully mapped to equities in Compustat at multiple points during the sample period with an interim of three to four years. The mapped percentage has increased over the year and reached over 80% at the end of 2017 for IG and HY combined.

Following the same methodology of sensitivity matching, we constructed replication portfolios using the equity portfolio, euro 7–10y Treasury index, and cash based on factor sensitivities calculated from trailing 36m regressions.[21] Panel B of Table 1.11 reports the performance of the bond, the replication, and the bond-over-replication portfolios in European markets. The performance numbers show a similar pattern of bond outperformance over the replication portfolios. Returns of the bond and their replication portfolios also have similarly high correlations as in the US market, ranging from 0.58 to 0.69. Despite the high correlations, the bond portfolios have higher average returns and Sharpe ratios than the replication portfolios, similar to the US markets. Moreover, the information ratios of bond-over-replication portfolio are positive at about 0.4 for IG and 0.7 for HY. The results are consistent across different weighting schemes. Overall, the results suggest that the bond outperformance also is present in European markets.

APPENDIX 1.3

Tests for Other Explanations of Bond-over-Equity Outperformance

This appendix provides detailed analysis of a few tests on some possible explanations for the bond-over-equity outperformance we documented.

Are Outliers Driving the Bond-over-Equity Outperformance? A Look at the Cross-Section

In the portfolio analysis, we find that the bond portfolios outperformed the replication portfolios with similar risk exposures. It is possible that the average bond outperformance was driven by a small number of firms but was not prevalent in the cross-section. To assess whether this is the case, we conducted pairwise comparisons on performance of bonds and the risk-matched-equity returns from the same company. The risk-matched-equity returns for each company are a combination of the 10yr Treasury, cash, and the equity from the same company. We determine the weights on Treasuries, cash, and the same-company equity in two approaches. In the first, we use the same weights from the portfolio analysis with trailing OLS regressions calculated each month from IG and HY portfolios, respectively (empirical hedge ratio[22]). One caveat of this approach is that each month it applies the same set of weights across the board for all companies in IG and HY, respectively, while in reality there are cross-sectional differences in the exposures to equity and Treasuries across bonds from different issuers. To incorporate the cross-sectional differences in risk sensitivity, we look at a second approach that takes into consideration each individual issuer's characteristics. In the second approach, for weights on equities we use the analytical hedge ratios based on the Merton model, and for weights on Treasuries we use the ratio of the average analytical duration of an issuer's bonds[23] to the duration of the 10y Treasury index as weights. Although the second approach incorporates individual companies' characteristics, earlier analysis such as Table 1.7 suggests that, at the portfolio level, the empirical hedge ratios are more effective than the analytical hedge ratios as the empirical hedge ratios lead to more volatility reduction and create more risk exposures similar to the bond portfolio. To balance out the trade-off between the hedge ratio efficacy and lack of cross-section variation, the subsequent analysis presents results using both approaches.

Table 1.12 shows the fraction of companies whose bonds had higher average returns compared with their risk-matched equities in the whole sample period as well as in each of the five-year subperiods. In the cross-section from 1993 to 2019, using empirical hedge ratios, 81% of IG and 77% of HY companies have bonds outperforming their risk-matched equities. In the subperiods, the fraction of companies with bond outperformance ranged from 55% (2003–2007 IG, 1998–2002 HY) to 88% (2008–2012 HY). The numbers suggest that across the sample, the majority of companies had bonds that outperformed their risk-matched equities, indicating that the bond outperformance at the portfolio level was unlikely to be driven by a handful of outliers.

Are We Underweighting Equity Risk?

Another possible explanation of the bond outperformance over the risk-matched equities is that the risk was not matched properly and bonds have higher returns as a compensation for the higher risk they carry. To examine whether this is the case, we look at the cross-sectional distribution of the pairwise volatility ratio (bond over risk-matched equity) for each company and its relation to the pairwise return differences. If the higher returns in bonds are a compensation for their higher risk (proxied by volatility), then we should expect to see a positive relation between the pairwise return difference and volatility ratio, as relatively riskier bonds (higher volatility ratio) should have more outperformance over the risk-matched equity from the

TABLE 1.12 Percentage of Positive Pairwise Return Differences (Bond-over-Risk-Matched Equities)

		Using Empirical Hedge Ratios (OLS Based)		Using Analytical Hedge Ratios (Merton Model)	
	Period	**IG**	**HY**	**IG**	**HY**
Whole Sample	Jan. 1993–Dec. 2019	81%	77%	84%	73%
Subperiod	Jan. 1993–Dec. 1997	82%	79%	84%	68%
	Jan. 1998–Dec. 2002	71%	55%	65%	55%
	Jan. 2003–Dec. 2007	55%	71%	71%	68%
	Jan. 2008–Dec. 2012	87%	88%	78%	70%
	Jan. 2013–Dec. 2019	75%	72%	93%	81%

Note: The returns are from January 1993 to December 2019. The analytical hedge ratios use the Merton (1974) implied hedge ratios for equities and the ratio of bond analytical duration to the 10yr Treasury analytical duration as the hedge ratio for Treasuries. The empirical hedge ratios use the portfolio-level hedge ratios that match the 2-factor (S&P500 and 10yr Treasury) sensitivities of the bond portfolio (EW) where the sensitivities are calculated from trailing 36m regressions.
Source: Bloomberg, Compustat, Barclays Research

same issuer (higher return difference). Panel A of Table 1.13 shows the summary statistics of the cross-sectional volatility ratio. The average volatility ratios are indeed slightly higher than one, but the median volatility ratios are fairly close to one, except IG companies using empirical hedge ratio. Panel B of Table 1.13 shows the results of regressing pairwise average return differences of bond over risk-matched equity on the pairwise volatility ratios in the cross-section. Contrary to the hypothesis, we see either a negative or an insignificant coefficient on the volatility ratio, which suggests that in the cross-section, companies with a higher volatility ratio of bond over risk-matched equity do not have a higher return difference, suggesting that the bond outperformance is not compensation for their higher risk.

Is Liquidity Driving the Bond Outperformance?

Credit markets are known to be relatively illiquid compared to equity and Treasury markets. Is it possible that the bond outperformance we find is a compensation for its illiquidity? We try to address this question in three ways. In the first approach, we perform the same set of analysis on a more liquid subsample: companies with stocks in the S&P 500. In the second

TABLE 1.13 Summary Statistics and Regression Results of Pairwise Volatility Ratios

Panel A. Cross-Sectional Summary Statistics of Pairwise Volatility Ratio (Bond over Risk-Matched Equity)				
	Using Empirical Hedge Ratios (OLS Based)		Using Analytical Hedge Ratios (Merton Model)	
Statistic in Cross-Section	**IG**	**HY**	**IG**	**HY**
Average	1.27	1.10	1.09	1.10
Standard Deviation	0.49	0.59	0.26	0.43
25%tile	0.97	0.72	0.93	0.80
Median	1.18	0.96	1.02	1.03
75%tile	1.47	1.30	1.17	1.30
% of Companies w. Vol. Ratio <=1	29%	55%	44%	47%

(Continued)

TABLE 1.13 (*Continued*)

Panel B. Cross-Sectional Regression of Pairwise Average Monthly Return Difference on Pairwise Volatility Ratio (Bond over Risk-Matched Equity)				
Independent Variables	**Using Empirical Hedge Ratios (OLS Based)**		**Using Analytical Hedge Ratios (Merton Model)**	
	IG	**HY**	**IG**	**HY**
Intercept	0.245***	0.715***	0.218***	0.327***
Volatility Ratio (Bond/Risk-Matched Equity)	–0.11***	–0.458***	–0.09*	–0.097*
Adj. R^2	6%	17%	2%	0%

Note: The returns are from January 1993 to December 2019. The analytical hedge ratios use the Merton (1974) implied hedge ratios for equities and the ratio of bond analytical duration to the 10yr Treasury analytical duration as the hedge ratio for Treasuries. The empirical hedge ratios use the portfolio-level hedge ratios that match the 2-factor (S&P500 and 10yr Treasury) sensitivities of the bond portfolio (EW) where the sensitivities are calculated from trailing 36m regressions. Companies with less than 24 months of observations are eliminated from the sample of volatility ratio calculation. Individual volatility ratios are winsorized at 99%tile to eliminate the impact of outliers on the regression.
Source: Bloomberg, Compustat, Barclays Research

approach, we sort companies into different buckets based on the liquidity of their bonds and test whether there is any difference in bond outperformance in different liquidity buckets. In the third approach, we take into consideration transaction costs of trading bonds and examine whether the bond portfolio still has any outperformance over its replication portfolio made of equities and Treasuries. In all three approaches, we find similar bond outperformance.

Test 1: Performance in the S&P 500 Subsample

In the first approach, we focus on a subsample with liquid bonds and equities: S&P 500 companies with publicly traded bonds included in the Bloomberg Barclays Corporate and HY index. We perform the similar analysis of bond vs. replication portfolio comparison for this subsample. If bond illiquidity is a main driver behind its outperformance, we would expect this liquid sample to have very limited bond outperformance. Figure 1.14 shows the percentage of S&P 500 market capitalization that have mapped index bonds. The coverage ratios indicate that the majority of the S&P 500 have mapped index bonds, with the percentage covered approximately 90% in 2014 and onward. Table 1.14 shows the performance of the bond-over-replication portfolios for this subsample. The last column shows the correlation between the bond portfolio and its replication portfolio, respectively, for each weighting scheme. The correlations are fairly high, ranging from 0.71 to 0.80, depending on the weighting scheme, indicating that our

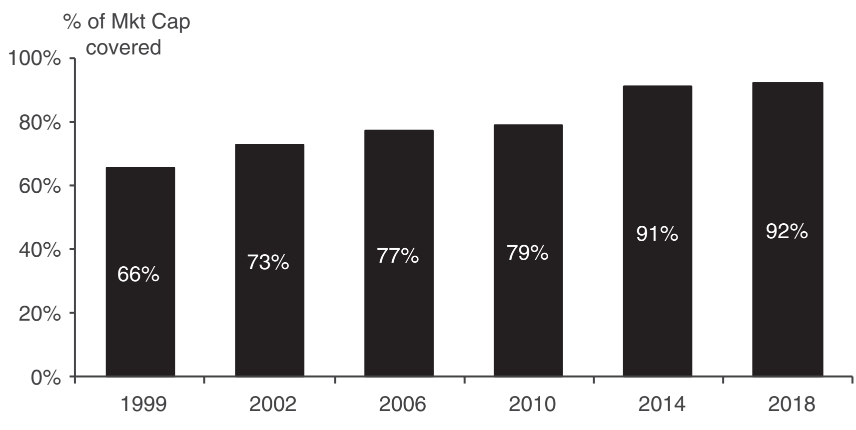

FIGURE 1.14 Percentage of Market Cap of S&P 500 Stocks Having Mapped Index Bonds
Source: Bloomberg, Compustat, Barclays Research

risk-matching methodology does a decent job for this subsample as well. Regardless of the weighting scheme, the bond portfolios outperformed the replication portfolios, delivering higher average returns by 1.70 to 1.90% per year with information ratios between 0.49 and 0.57. As the numbers suggest, the bond portfolios outperform their replication portfolios in the S&P 500 subsample with a magnitude similar to the IG universe.

Test 2: Rank Companies by Their Bond Liquidity

In the second approach, we used Liquidity Cost Score (LCS)[24] as a proxy for bond liquidity. Each month, we divided all issuers into low and high LCS categories and tracked their performance in a similar way as in earlier analysis. If bond liquidity is the reason for bond outperformance, we would expect the bond portfolio in the low-liquidity bucket to have greater outperformance over the replication portfolio than the bond portfolio in the high-liquidity bucket. Table 1.15 shows the performance of bond-over-replication portfolios by LCS ranking. In low and high LCS buckets, bond-over-replication portfolios have similar information ratios in both IG and HY and across weighting schemes. The similar magnitude of bond outperformance across LCS buckets suggests that liquidity is not likely to be a reason for bonds' outperformance over equities.

Test 3: Incorporating Bond Transaction Costs

In the third approach, we take out transaction costs in the bond portfolios, using LCS as a proxy for transaction costs.[25] Panel A of Table 1.16 compares the gross with the net performance of the bond portfolio and the bond-over-replication portfolio, and Panel B reports the average transaction cost and holding period for the bonds in the bond portfolio. We did not account for any transaction costs for the equity and Treasury portfolio, which puts the bond portfolio at a disadvantage. The table shows that after accounting for transaction costs in bonds, the bond-over-replication portfolio outperformance deteriorates slightly, but by a small magnitude (9bp/yr in IG and 50bp/yr in HY). The results suggest that average transaction cost per year is small compared to the returns of the bond portfolio. This is because the securities in the bond portfolio have fairly long holding periods, as shown in Panel B of Table 1.16 (5.9 yr for IG and 3.5 yr for HY). The average transaction costs would be small after spreading over the entire holding period. As a result, incorporating transaction costs in bonds made only a very small difference in the bond outperformance over equities. The information ratios of the net returns of bond-over-replication portfolios remain strong at 0.51 for IG and 0.73 for HY. Results are similar across weighting schemes.

TABLE 1.14 Performance of Bond over Replication Portfolio for S&P 500 Subsample

Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Inf. Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)	Corr. (Bond, Replication Portfolio)
EW	1.90	3.38	0.56	–2.93	–10.98	0.73
Bond-VW	1.85	3.77	0.49	–5.43	–8.26	0.71
Equity-VW	1.70	2.96	0.57	–3.35	–7.95	0.80
Total-VW	1.74	3.09	0.56	–3.68	–7.85	0.79

Note: The portfolio returns are from January 1993 to December 2019. Weights on equity, 10y Treasury, and T-bills calculated monthly from EW bond and equity portfolios using sensitivity matching of two factors (S&P 500 and 10y Treasury Ret).
Source: Bloomberg, Compustat, Barclays Research

TABLE 1.15 Performance of Bond over Replication Portfolios by LCS Ranking

	LCS Ranking	Avg. Ret. (%/yr)	volatility (%/yr)	Inf. Ratio (Ann.)	Worst Monthly Ret. (%/m)	Max. Drawdown (%)
IG	Low LCS (high liquidity)	1.45	1.74	0.83	–1.12	–2.40
	High LCS (low liquidity)	2.45	3.08	0.79	–1.99	–7.05
HY	Low LCS (high liquidity)	3.86	2.87	1.35	–1.73	–3.70
	High LCS (low liquidity)	5.41	4.98	1.09	–3.92	–6.66

Note: Portfolios returns are from January 2010 to December 2019. Analysis starts in 2007 due to availability of LCS data. All portfolios are equally weighted among individual securities.
Source: Bloomberg, Compustat, Barclays Research

Overall, accounting for bond liquidity, by focusing on a liquid subsample such as S&P 500 firms, by ranking issuers by the liquidity of their bonds, or by taking out bond transaction costs, seems to have limited effect on the bond outperformance over replication portfolios. These sets of results suggest that bond liquidity is not likely to be a driving force for bond outperformance.

Using Moving Average and Forward-Looking Window in Calibrating Weights for Replication Portfolios

Some are concerned that the correlations between bond and equities are higher during recessions. As a result, using a trailing window to calibrate the weights for equities may underweight equities in the replication portfolio during recessions and lead to overall bond outperformance. To rule out this hypothesis, we reconstruct the replication portfolio using two alternative windows to calculate the weights for equities and Treasuries:

1. A moving average window centered on the calibration month (denoted as centered)
2. A forward-looking window starting on the calibration month (denoted as forward)

TABLE 1.16 Transaction Costs and Net Performance

Panel A. Gross and Net Performance of Bond-over-Replication Portfolios

	IG						HY					
	Bond			**Bond-over-Replication Portfolio**			**Bond**			**Bond-over-Replication Portfolio**		
	Avg. Ret. (%/yr)	**Volatility (%/yr)**	**Sharpe Ratio (Ann.)**	**Avg. Ret. (%/yr)**	**Volatility (%/yr)**	**Inf. Ratio (Ann.)**	**Avg. Ret. (%/yr)**	**Volatility (%/yr)**	**Sharpe Ratio (Ann.)**	**Avg. Ret. (%/yr)**	**Volatility (%/yr)**	**Inf. Ratio (Ann.)**
Gross	5.90	5.03	**0.95**	2.02	3.76	**0.54**	7.40	8.03	**0.78**	4.69	5.73	**0.82**
Net of Transaction Costs	5.81	5.04	**0.94**	1.93	3.75	**0.51**	6.89	8.15	**0.71**	4.18	5.76	**0.73**

Panel B. Average Bond Transaction Cost and Holding Horizon

	Annualized Bond Transaction Cost (%)	**Average LCS (%)**	**Average Bond Holding Period (Yr)**
IG	0.09	1.02	5.9
HY	0.50	1.56	3.5

Note: Portfolios returns are from January 2007 to December 2019. Analysis starts in 2007 due to availability of LCS data. All portfolios are equally weighted among individual securities.
Source: Bloomberg, Compustat, Barclays Research

TABLE 1.17 Performance Statistics of Bond-over-Replication Portfolio Return Differences by Replication Window in Calibrating Weights on Equities and Treasuries

	Replication Window	Avg. Ret. (%/yr)	Volatility (%/yr)	Inf. Ratio (Ann.)	Worst Monthly Ret. (%)	Max. Drawdown (%)
IG	Trailing (Original)	1.60	3.06	**0.52**	–3.11	–13.52
	Centered	1.88	2.55	**0.74**	–3.37	–8.28
	Forward	1.72	2.46	**0.70**	–3.69	–10.13
HY	Trailing (Original)	3.37	5.27	**0.64**	–6.64	–17.10
	Centered	4.00	4.32	**0.93**	–7.10	–13.37
	Forward	3.84	4.14	**0.93**	–7.37	–12.21

Note: Return periods are from January 1993 to January 2017 for an overlapping sample between three types of replication windows.
Source: Bloomberg, Compustat, Barclays Research

TABLE 1.18 Portfolio Performance Adjusted for Autocorrelations in Volatilities

Portfolio		Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
IG	Bond	EW	6.48	5.74	0.70	–8.22	–13.80	
		Bond-VW	6.20	5.86	0.64	–6.84	–14.23	
		Equity-VW	6.37	5.59	0.71	–6.54	–11.61	
		Total-VW	6.35	5.63	0.70	–6.42	–11.99	
	Replication Portfolio	EW	4.85	4.79	0.52	–5.81	–9.04	0.82
		Bond-VW	4.64	4.98	0.45	–8.53	–15.93	0.78
		Equity-VW	4.81	4.86	0.50	–6.93	–10.07	0.85
		Total-VW	4.78	4.87	0.49	–7.26	–10.58	0.84
	Bond over Replication	**EW**	**1.63**	**3.27**	**0.50**	**–3.11**	**–13.52**	
		Bond-VW	**1.56**	**3.56**	**0.44**	**–5.67**	**–9.61**	
		Equity-VW	**1.56**	**2.99**	**0.52**	**–3.59**	**–8.11**	
		Total-VW	**1.57**	**3.07**	**0.51**	**–3.90**	**–8.10**	

(Continued)

TABLE 1.18 (*Continued*)

Portfolio		Weighting Scheme	Avg. Ret. (%/yr)	Volatility (%/yr)	Sharpe (Inf.) Ratio (Ann.)	Worst Monthly Ret (%)	Max. Drawdown (%)	Corr. w. Bond Portfolio
HY	Bond	EW	7.99	8.46	0.65	–15.58	–25.13	
		Bond-VW	7.62	7.99	0.65	–13.51	–24.80	
		Equity-VW	8.03	6.75	0.82	–13.36	–19.98	
		Total-VW	7.95	7.09	0.77	–13.40	–21.28	
	Replication Portfolio	EW	4.56	6.29	0.35	–8.94	–22.69	0.68
		Bond-VW	5.20	6.41	0.44	–10.42	–22.06	0.72
		Equity-VW	4.68	4.82	0.48	–8.47	–16.79	0.70
		Total-VW	4.88	5.25	0.48	–9.01	–17.96	0.71
	Bond over Replication	**EW**	**3.43**	**5.18**	**0.66**	**–6.64**	**–17.10**	
		Bond-VW	**2.42**	**5.06**	**0.48**	**–4.50**	**–13.52**	
		Equity-VW	**3.34**	**4.56**	**0.73**	**–4.90**	**–8.20**	
		Total-VW	**3.07**	**4.64**	**0.66**	**–4.40**	**–9.41**	

Source: Bloomberg, Compustat, Barclays Research

Besides the positioning of the window relative to the calibration month, other aspects of the calculation methods are similar to the original specification: Both windows have the same length (36m), exponentially decay weighting with a half-life of 9m, and assigning the calibration month the most weight.

Results are shown in Table 1.17. The performance statistics cover the sample period of January 1993 to January 2017, when the time series of the replication portfolio returns overlap among the three calibration windows.[26] The patterns of return comparisons are very similar to the original results, indicating that the time dynamics of the correlations between bonds and equities are not a driving force behind the bond outperformance.

Adjusting for Autocorrelation in Computing Portfolio Returns Did Not Account for Higher Sharpe Ratio in Bonds

There might be high autocorrelation in bond monthly returns, which increases volatilities of the bond portfolios. We adjust for possible serial correlation in the volatilities in the bond, replication, and the bond-over-replication portfolios (results shown in Table 1.18).[27] Bond portfolios still have considerably higher Sharpe ratios than the equity portfolios in both IG and HY, regardless of the weighting schemes used.

NOTES

1. Capital market information provided by SIFMA can be found at www.sifma.org.
2. Merton (1974) lays out a framework where the payoffs to bonds and stocks are driven by the same underlying asset value and derives the link between the two types of securities. Merton's model implies that a corporate bond is represented by a risk-free bond and a short put position on the underlying assets of the firm while the company's stock is represented by a call option on the firm.
3. Studies such as Bakshi and Kapadia (2003) and Carr and Wu (2009) found that a short volatility position on equities generates on average a positive risk premium, termed the equity variance risk premium.
4. Call provisions are more likely to be exercised when interest rates decline and bond prices rise. Hence, the impact of call features is similar to holding put options on interest rates for bond issuers and vice versa equivalent to shorting put options on interest rates and having a short exposure to interest rate volatility for bondholders.
5. Each month *s* we run the following regression using trailing 36m data with exponentially decayed weighting (half life=9m, but results are robust to use equal weighting or other half lives):

$$\text{Credit Index Total Ret}_t = \alpha + w_E * \mathrm{Ret}_t^{S\&P\ 500} + w_{Treasury} * \mathrm{Ret}_t^{Treasury\ Index} + \varepsilon_t, where\ t = s-36,\ldots,s-1$$

Any access weight is allocated in T-bills: $w_{T-Bills} = 1 - w_E - w_{Treasury}$

6. The process of creating the bond–equity mapping is discussed in great detail in Ben Dor and Xu (2015).
7. The results have no material difference from the results when we include all bonds with no price filters.
8. All index bonds of the same issuer are aggregated to issuer level using bond market value as weights.
9. The results using the Treasury Index are qualitatively similar to that using the 10-yr OTR but the replication portfolio performed slightly better when it uses the Treasury index than when it uses the 10-yr Treasuries. This is because the Treasury index outperformed the 10-yr Treasuries on a duration-matched base.
10. The results are similar using 48m or 60m trailing window and using equal-weighting instead of exponential decay weighting. The results are also similar using different half-life (currently 9m) of the exponential decay weighting. The exponential decay weighting is to ensure that we don't have big monthly changes in the weights when certain months with large effects are suddenly dropped out of the trailing window.
11. Step1: Estimate factor sensitivities in month *t* using regressions and trailing 36m data:

$$Ret_s^{Bond} = Intercept_{Bond,t} + \beta_{Bond,t} * SP500_s + \gamma_{Bond,t} * 10yTreasury_s + \varepsilon_{Bond,s}$$

$$Ret_s^{Equity} = Intercept_{E,t} + \beta_{E,t} * SP500_s + \gamma_{E,t} * 10yTreasury_s + \varepsilon_{E,s},$$
$$where\ s = t-36,..,t-1$$

Step 2: Solve for weights on equities, 10-yr treasuries, and 3m T-bills:

$$Replication\ Portfolio = W_{E,t} * Equity + W_{T,t} * 10yTreasury + W_{RF,t} * 3mTbill,$$

We solve for the two unknowns $(W_{E,t}, W_{T,t})$ in two equations: 1) $\beta_{Bond,t} = W_{E,t}\beta_{E,t}$, 2) $\gamma_{Bond,t} = W_{E,t}\gamma_{E,t} + W_{T,t}$, and any excess is allocated in the 3m T-bills: $W_{RF,t} = 1 - W_{E,t} - W_{T,t}$.
12. Vol.-Matched Replication Portfolio = *HR* * *Equity Portfolio* + *(1 − HR)* $*3mTbillRet$, where $Hedge\ Ratio\ HR = \dfrac{Vol(Bond\ Portfolio\ Ret)_{t-36,t-1}}{Vol(Mapped\ Equity\ Portfolio\ Ret)_{t-36,t-1}}$

13. The analytical hedge ratio is:

$$Hedge\ Ratio_{equity} = \frac{\frac{\partial D}{D}}{\frac{\partial E}{E}} = \left(\frac{\frac{\partial D}{\partial V}}{\frac{\partial E}{\partial V}}\right)\frac{E}{D} = \left(\frac{1-\frac{\partial E}{\partial V}}{\frac{\partial E}{\partial V}}\right)\frac{E}{D} = \left(\frac{1}{\frac{\partial E}{\partial V}} - 1\right)\frac{E}{D}$$

where $\frac{\partial E}{\partial V} = N(d1), N(.) \textit{ is the normal cdf function}$

$$d1 = \frac{\ln\left(\frac{V}{book\_debt}\right) + \left(rf + \sigma^2/2\right)T}{\sigma\sqrt{T}}$$

book_debt: long-term debt from Compustat; D: market value of long-term debt, calibrated as $\frac{\text{MV\_index bonds}}{\text{AmtOutstanding\_index bonds}}$ * book_debt; E: market value of equity; V = D+E; rf: 3m Libor; σ^2: asset volatility =

$$\left(\frac{E}{V}\right)^2 \sigma^2_{E(option\ implied,\ ATM)} + \left(\frac{D}{V}\right)^2 \sigma^2_{D(DTS)} + 2\left(\frac{E}{V}\right)\left(\frac{D}{V}\right) Corr_{DE}\sigma_E\sigma_D$$

14. Alternatively, we could estimate empirical durations as a function of analytical durations, as suggested in prior QPS studies, but such a method would estimate bonds' sensitivity to interest rate risk in isolation of their sensitivities to the market factor. The market factor in reality has a negative exposure to treasuries on average, but positive in a small number of months. Similarly, the credit component in HY bonds, which has high correlation with the market factor, on average should have a negative sensitivity to yield changes, which is partly the reason why empirical durations of HY bonds are much lower than their analytical durations. To dynamically account for both the market risk and interest rate risk in an unbiased manner, we should include both risk factors simultaneously in the OLS regressions, which is exactly what we did in sensitivity matching.
15. SPX option data is from OptionMetrics and available since January 1996. Option returns are calculated as:

$$Option\ Return_t = \frac{OptionPrice_t - OptionPrice_{t-1} - Delta_{t-1}\left(SPXFuture_t - SPXFuture_{t-1}\right)}{SPX\ Spot_{t-1}}$$

16. Treasure option data is from CME. Treasury option returns are calculated as:

$$Option\ Return_t = \frac{OptionPrice_t - OptionPrice_{t-1} - Delta_{t-1}\left(TreasuryFuture_t - TreasuryFuture_{t-1}\right)}{Treasury\ Future_{t-1}}$$

17. The BAB factor longs low-beta stocks and shorts high-beta stocks and makes the factor market-neutral by leveraging up the low-beta leg.
18. The exposure estimates are based on the regression coefficients on the Equity VRP and Bond VRP (puts) reported in Table 1.8. The reported numbers are the average coefficients of IG and HY to simplify the illustration. For example, coefficient 0.5 means that for each $1 value change in a $100 notional position in the short volatility strategy (e.g., equity VRP or Bond VRP), the value change in a $100 market value position in bonds would be $0.50. In other words, to replicate the exposures in a $100 market value position of bonds, we would need $100*0.5 =$50 in the underlying notional for each short volatility strategy.
19. To calculate the $ amount of the corporate bonds whose volatility exposures the option strategy can replicate (call it x), for each option market we solve for x from the equation: Exposure coefficient*x = 5%*Daily volume/2. We divide the daily volume by 2 because the daily volume accounts for both calls and puts, and the replication strategy would require one of each.
20. Ben Dor, Guan, and Zeng (2018) provides details on the European mapping.
21. For European markets, we proxy for the market risk factoring using the Stoxx 600 index returns and the interest rate risk using the Bloomberg Barclays Euro 7–10yr Treasury index.
22. We used the weights calculated from equally weighted bond and equity portfolios. Results using other weighting schemes are similar.
23. Each month, returns of all index bonds of the same company are aggregated into one return number using bond market values as weights.
24. Liquidity Cost Score (LCS) measures the cost of an immediate, institutional-size, round-trip transaction, expressed as a percentage of the bond's price. LCS is computed based on bond-level quotes. (See Konstantinovsky, Ng, and Phelps 2016 for more details.)
25. LCS is expressed as a percentage of a bond's price and is taken out from a bond's return when the bond leaves the portfolio.
26. Since the forward window requires the subsequent 36m to calibrate for the current month, the last observation for the replication portfolio is January 2017, 36 months before the end of the sample period (December 2019). Since this sample period is 36m shorter than the original sample period, the performance for the trailing window is also slightly different from originally reported in Table 1.4.
27. To account for first-order autocorrelation in monthly returns, the annualized volatility is calculated as volatility in monthly returns multiplied by the squared-root of (12+2*11*AR1), where AR1 is calculated from regressions of monthly returns on the lagged one-month returns: $r_t = a + AR1 * r_{t-1} + \varepsilon_t$.