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Modeling Corporate Bond Returns

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ABSTRACT

We propose a conditional factor model for corporate bond returns with five factors and time-varying factor loadings. We have three main empirical findings. First, our factor model excels in describing the risks and returns of corporate bonds, improving over previously proposed models in the literature by a large margin. Second, our model recommends a systematic bond investment portfolio whose high out-of-sample Sharpe ratio suggests that the credit risk premium is notably larger than previously estimated. Third, we find closer integration between debt and equity markets than found in prior literature.

As of 2019, global bond markets' outstanding value was \$105.9 trillion, whereas global equity market capitalization was \$95 trillion (SIFMA (2020)). In the United States, there was approximately \$9.5 trillion of U.S. corporate debt outstanding, compared to \$30 trillion in market capitalization of U.S. public equities. U.S. corporate bond issuance totaled roughly \$1.4 trillion in 2019, versus \$228 billion for U.S. equity. Despite the similarity in their size and importance to the economy, however, academic understanding of the risk-return trade-off is less developed in corporate bond markets than in equity markets.

Recent literature has started to map out a factor structure in corporate bond returns. For instance, Bai, Bali, and Wen (2019) (BBW) propose portfolio-sorted corporate bond factors. This research largely follows the Fama and French (1993) and Fama and French (2015) (FF) blueprint for equities. This approach first defines ad hoc factors as long-short portfolios based on characteristics that predict the cross section of bond returns (e.g., value or profitability). It

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then tests whether exposures to the factors help explain differences in average returns across bonds.

We propose a new conditional factor model for individual corporate bond returns based on instrumented principal components analysis, or "IPCA" (Kelly, Pruitt, and Su (2019, KPS)). We have three main empirical findings. First, our factor model excels in describing the risks and returns of corporate bonds, improving over previously proposed models in the literature by a large margin. Second, our benchmark model recommends a systematic bond investment portfolio that significantly outperforms leading corporate credit investment strategies. Its high out-of-sample Sharpe ratio suggests that the credit risk premium is notably larger than previously estimated. Third, we find evidence of closer integration between debt and equity markets than documented in prior literature.

Our model has two major differences compared to the prior literature on corporate bonds. First, rather than prespecifying ad hoc factors, we treat factors as unobservable and estimate the factors that best describe covariation among bond returns. When researchers prespecify factors and treat them as observable versions of the "true" underlying factors, they fail to account for measurement and specification error, which biases inference about the asset pricing model. By acknowledging that the true factors are unobserved, our estimation approach searches for the most appropriate factors and avoids inferential complications from fixing factors ex ante and treating them as perfectly observed.

Second, we parameterize factor betas to depend on observable firm and bond characteristics. These serve as instruments that make it possible to estimate time-varying conditional betas. This contrasts with the standard approach of estimating factor betas by conducting time-series regressions on observable factors. Time-series regressions by their very nature estimate static betas and thus restrict the researcher to analyzing unconditional asset pricing models. But a large literature documents that risk exposures tend to fluctuate rather dramatically over time.[1] Attempts to introduce time-variation in betas with rolling time-series regression lead to stale and noisy beta estimates. Others use instrumented betas but require observable factors.[2] IPCA jointly estimates latent factors and bonds' exposures to these factors by leveraging information in observable bond characteristics, delivering consistent and efficient estimation of both.

Because IPCA betas can depend on a potentially large number of characteristics, we are able to address a number of other empirical challenges to modeling the cross section of returns. For example, the literature typically constructs observable factors based on a small number of characteristics that are selected ex ante. When different researchers propose and study their own distinct factors in isolation, we inevitably end up with a "factor zoo" problem (Cochrane (2011)). By estimating a model that jointly analyzes many characteristics at

[1] See, among others, Jagannathan and Wang (1996), Santos and Veronesi (2004), Lewellen and Nagel (2006), Ang and Kristensen (2012), and Engle (2016).

[2] See Ferson and Harvey (1999) and Avramov and Chordia (2006).

the same time, IPCA allows the data to dictate which characteristics are most informative for understanding the panel of bond returns. While this is helpful for identifying informative characteristics, it also helps solve the more difficult problem of how to aggregate information over a large collection of bond characteristics that are all likely to be informative, but also noisy and thus imperfect, determinants of a bond's risk exposures.

These model features—latent factors and instrumented betas—drive large gains in our understanding of the risk-return trade-off in corporate bond markets. We focus attention on a benchmark five-factor model in which characteristics affect expected returns only through factor exposures. To quantify the success of our model, we focus on three dimensions of empirical performance. First, a successful factor model should excel in describing the common variation in realized returns, that is, it should accurately describe systematic risks. We measure this according to a factor model's "total R^2," which describes the fraction of variation in the panel of bond returns that is explained by the common risk factors. Our main five-factor IPCA model explains 51% of the panel variation in monthly individual bond returns *out-of-sample*. We focus on out-of-sample performance because some of the benchmark models are very highly parameterized, leading to in-sample overfit and poor out-of-sample generalizability. For comparison, the FF five-factor model and BBW four-factor model have essentially zero out-of-sample explanatory power for individual bonds. In other words, our model provides an especially accurate portrayal of the aggregate riskiness of corporate bond returns relative to existing literature.

Our second assessment examines the size of the pricing errors from each model. In particular, we report a "relative pricing error" statistic that measures the magnitude of alphas relative to the magnitude of average returns. Relative pricing error is zero when the factor model fully explains differences in average returns across assets and is 100% if the factors explain none of the average returns. When we use individual bonds as test assets, the out-of-sample relative pricing error in our five-factor IPCA model is 39%, versus 76% for the FF model and 100% for the BBW model. When the test assets are 30 characteristic-managed bond portfolios, the out-of-sample relative pricing error from IPCA is 3%, versus 38% for the FF model and 106% for the BBW model.[3] We find similar results for other test assets such as size/maturity-sorted portfolios and industry portfolios (as suggested by BBW).

Our third model assessment studies the investment performance of systematic bond portfolios in terms of out-of-sample annualized Sharpe ratio. One such systematic strategy that we examine is a long-short quintile spread portfolio based on each model's estimated expected returns. This strategy is long bonds in the highest quintile of model-based expected returns and short bonds in the lowest quintile. It is here the IPCA model most clearly differentiates itself from alternatives. Its quintile spread portfolio earns an annualized out-of-sample Sharpe ratio of 3.5 prior to transaction costs, or 1.4 net of costs (based on transaction cost estimates from Choi and Huh (2019)). Another systematic

[3] In out-of-sample analysis, relative pricing error can exceed 100%.

strategy is the out-of-sample tangency portfolio of factors within each model, which corresponds to the model-implied multifactor mean-variance efficient portfolio. Theoretically, the true factor model maps to the economy's maximum Sharpe ratio portfolio and stochastic discount factor via this multifactor tangency portfolio. The factor tangency portfolio in the IPCA model earns an annualized out-of-sample gross Sharpe ratio of 6.2, or 2.5 net of trading costs. For comparison, the out-of-sample gross Sharpe ratio of the equal-weight bond market portfolio is 0.3 for the market model, 0.4 for the tangency portfolio of BBW factors, and 0.7 for the tangency portfolio of FF factors.

In IPCA, the clearest way to understand the "identity" of estimated latent factors is to inspect the parameters that map characteristics into betas. Our estimates find that five characteristics are particularly important for the accuracy of IPCA fits: bond spread, bond volatility, duration, spread divided by distance-to-default (essentially a bond "value" characteristic), and a constant. To provide an interpretation of the estimated latent IPCA factors, we study a new bond pricing model with observable factors based on these five important characteristics. Four of the factors are long-short spread portfolios sorted on the four nonconstant characteristics. The fifth factor is an equal-weight bond market factor (corresponding to the constant characteristic). We show that this model achieves a good approximation of the IPCA model, confirming the interpretation of the IPCA factors as roughly coinciding with managed portfolios for those five influential characteristics.

In our last set of analyses, we use the systematic risk decomposition afforded by IPCA to establish a new structural perspective on the integration of corporate debt and equity markets. Building on the work of Schaefer and Strebulaev (2008), we show that debt and equity markets are roughly twice as integrated as previous estimates suggest if we focus on the systematic (factor-related) components of bond and stock returns, and have an integration of almost zero when measured by the idiosyncratic components of returns. This finding favors theories of integration breakdown based on limits to arbitrage, and indicates that investor segmentation is a comparatively smaller impediment to integration. This conclusion is corroborated by our analysis of risk premia across markets. We build on Choi and Kim (2018) and study how expected bond returns behave in a model that uses only bond market factors, versus an "integrated" model that uses factors from the equity market. We find a stunningly close association—a correlation upward of 80%—in the estimates of expected bond returns from these two models. These results convey a notably brighter perspective on the integration of corporate bond and stock markets relative to prior empirical work.

In addition to BBW, our work is related to Gebhardt, Hvidkjaer, and Swaminathan (2005a) and Elkamhi, Jo, and Nozawa (2020) who study observable factor models in the bond market. It is also related to a large literature investigating characteristics and bond returns (including Correia, Richardson, and Tuna (2012), Jostova et al. (2013), Chordia et al. (2017), Chung, Wang, and Wu (2019), He, Khorrami, and Song (2020), Bartram, Grinblatt, and Nozawa (2020), Bali et al. (2020), Bali, Subrahmanyam, and Wen (2021), among others), and to a large literature studying changes in corporate credit spreads (Collin-Dufresne, Goldstein, and Martin (2001), Elton et al. (2001), Nozawa (2017) for example)). Our paper is also related to literature on corporate bond portfolio choice, including Israel, Palhares, and Richardson (2018) and Bredendiek, Ottonello, and Valkanov (2019).

The paper proceeds as follows. Section I describes the IPCA procedure. It also describes existing factor models that we benchmark against and describes the various metrics we use to measure and compare model performance. Section II describes the data and provides preliminary descriptive evidence of return and covariance predictability based on characteristics. Section III reports the main empirical results for IPCA and compares across models. Section IV investigates the market integration and structural linkages between corporate debt and equity markets. Section V concludes.

I. Models

In this section, we briefly review the IPCA model, describe the benchmark models against which we compare, and describe our model performance metrics.

A. IPCA

Our empirical analysis centers around the IPCA model specification proposed by Kelly, Pruitt, and Su (2019) (2021). It is a conditional factor-pricing model in which betas and (if they exist) alphas are allowed to be time-varying and dependent on prevailing observable information. Our IPCA specification for an excess bond return $r_{i,t+1}$ is

$$r_{i,t+1} = \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1}, \quad \beta_{i,t} = z'_{i,t}\Gamma_{\beta}. \tag{1}$$

Individual bonds have dynamic factor loadings, $\beta_{i,t}$, on a K-vector of latent factors, f_{t+1}. The most important component of this model is the structure it uses for factor loadings. They are parameterized to depend linearly on observable asset characteristics in the $L \times 1$ instrument vector $z_{i,t}$ (which includes a constant).[4] In contrast to traditional factor models that rely only on returns data, IPCA relies on additional information beyond returns to shape the factor model. This allows the model to quickly update risk exposures based on the timely news in characteristics data, rather than having to rely on stale beta estimates from rolling regressions. And conditioning instruments, which are high dimensional and informationally rich, can make the estimation of exposures and factors more efficient.

[4] It is possible to include a bond-specific fixed component in the IPCA beta specification, essentially nesting PCA within IPCA. Unfortunately, in our sample with thousands of bonds, this expands the parameterization of IPCA by several orders of magnitude, resulting in a badly overfit and unstable model. Therefore, we do not consider bond-specific fixed components in our analysis.

We focus on model specifications in which the number of factors is small. The empirical content of the model lies in its enforcement of parsimony and in its assessment of which characteristics best proxy for risk exposure. The $L \times K$ matrix Γ_β achieves a dimension reduction from the large set of characteristics (dimension L) to the much smaller number of factor exposures ($K \ll L$). The mapping from characteristics to exposures provides a formal statistical bridge between characteristics and expected returns. Moreover, it imbues IPCA with a degree of parsimony unmatched by traditional factor models. As we show below, our preferred IPCA specification has many fewer parameters than competing observable factor models. IPCA's emphasis on dimension reduction exploits the fact that bonds possess many characteristics that are all likely to be informative, albeit noisy, signals about a bond's risk exposures. Aggregating characteristics into a few linear combinations therefore helps isolate their signal and average out noise.

One of our null hypotheses throughout the paper is that bonds are priced by a conditional factor model with no alpha. This corresponds to restricting conditional intercepts $\alpha_{i,t}$ to zero for all bonds at all points in time.[5]

To estimate IPCA, we find the values of $(\{f_{t+1}\}, \Gamma_\beta)$ that minimize the sum of squared model errors. The solutions satisfy first-order conditions

$$\hat{f}_{t+1} = \left(\hat{\Gamma}'_\beta Z'_t Z_t \hat{\Gamma}_\beta\right)^{-1} \hat{\Gamma}'_\beta Z'_t r_{t+1}, \quad \forall t \tag{2}$$

and

$$\operatorname{vec}(\hat{\Gamma}'_\beta) = \left(\sum_{t=1}^{T-1} Z'_t Z_t \otimes \hat{f}_{t+1}\hat{f}'_{t+1}\right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t \otimes \hat{f}'_{t+1}\right]' r_{t+1}\right), \tag{3}$$

where Z_t and r_{t+1} denote stacked arrays of bond instruments and returns, respectively. In other words, factor returns (2) are period-by-period cross-section regression coefficients of $r_{i,t+1}$ on $\beta_{i,t}$, just as in Fama and MacBeth (1973). Γ_β is the time-series regression coefficient of returns on the factors interacted with firm-specific characteristics.[6]

As KPS point out, the IPCA estimator can be loosely approximated by applying PCA to returns on L *characteristic-managed portfolios*, defined as

$$x_{t+1} = \frac{Z'_t r_{t+1}}{N_{t+1}}. \tag{4}$$

[5] In the Appendix, we also consider an alternative hypothesis that allows for nonzero $\alpha_{i,t}$, representing the possibility that conditional expected bond returns are predictable by characteristics but *not* through betas. Under the alternative hypothesis, IPCA estimates $\alpha_{i,t}$ by finding the linear combination of characteristics that best describes conditional expected returns while controlling for the role of characteristics in factor risk exposure. If characteristics align with average bond returns *differently* than they align with risk factor loadings, then IPCA will estimate a nonzero Γ_α vector, thus identifying compensation for holding bonds that does not align with their systematic risk exposure.

[6] As described in KPS, IPCA estimates are found via a fast-converging alternating least squares algorithm based on the first-order conditions above.

The l^{th} element of x_{t+1} is a portfolio with weights given by the value of the l^{th} characteristic for each bond at time t (normalized by the number of nonmissing bond observations each month, N_{t+1}). While the test assets for (1) are by definition individual corporate bonds, KPS point out that x_{t+1} plays a key role in the IPCA estimator. They show that IPCA can equivalently be viewed as using characteristic-managed portfolios x_t as the set of test assets, which have comparatively low dimensionality and average out a substantial degree of idiosyncratic bond risk. Throughout the paper, we report model performance based on individual bonds as test assets as well as on characteristic-managed bond portfolios as test assets. We find that a *single* IPCA bond factor model can be used to calculate fits for *both* sets of test assets. Furthermore, we can aggregate the individual bond fits to any other portfolio desired, something we do when considering size/maturity-sorted portfolios and industry portfolios as test assets.

A nuance of latent factor models such as IPCA is that individual factors are identified only up to a rotation because the models $\Gamma_\beta f_t$ and $\Gamma_\beta RR^{-1}f_t$ are identical when R is a rotation matrix. In other words, the K-factor IPCA model finds the K-dimensional space spanned by our factors, but a rotation of those factors does not change the fit of the model. We follow the identification scheme outlined by KPS and impose that $\Gamma'_\beta\Gamma_\beta$ is the identity matrix, that the unconditional second moment matrix of the factors is diagonal with descending diagonal entries, and that the mean of each factor is nonnegative. These assumptions have no impact on model fit, they merely pin down a uniquely identified solution to the estimation problem.

B. Benchmark Observable Factor Models and Their Estimation

We consider three different observable factor models from the literature as benchmarks in our analysis:

1. *MKT model*: We construct our own bond market factor as the equal-weighted average of excess bond returns in our data.[7] This produces a market factor that is best positioned to coincide with variation in our bond return panel.
   This model is motivated by Fama and French (1993), who in their original factor model propose combining three equity factors with two bond factors. Their first factor, DEF, is essentially the excess market portfolio of corporate bonds. We construct our own equal-weight market factor within our specific sample rather than use DEF. Their second bond factor, TERM, is the return on a risk-free bond maturity spread portfolio and is intended to capture cross-sectional patterns in government bond portfolios. This factor is not relevant for our sample as we strip out the

[7] Section II details construction of the bond returns.

risk-free bond return from our credit returns and thus we omit it from our analysis.[8]

2. *BBW* model: BBW propose and analyze a four-factor model for the cross section of bond returns. Their factors are returns to portfolios sorted on downside risk, credit risk, liquidity risk, and a value-weight bond market factor. These are available from the authors for a shorter sample (2004 to 2019) than our bond data. In what follows, our estimates of the BBW model use their shorter sample period.
3. *FF* model: As noted above, Fama and French (1993) test the ability of their model, including equity factors, to price corporate bond returns. More recently, Bektic et al. (2019) advocate the FF five-factor equity model for pricing the cross section of corporate bonds. In light of this and its general stature as a leading approximation of the stochastic discount factor for U.S. asset markets, we analyze the FF five-factor model as one of our observable factor benchmark models.

We estimate observable factor models treating betas as static parameters and, following the standard approach in the literature, estimate them using time-series regressions

$$r_{i,t+1} = \beta_{i,t}' g_{t+1} + \varepsilon_{i,t+1}, \tag{5}$$

where g_{t+1} denotes a vector of observable factors. Following the literature, $\beta_{i,t}$ is estimated in rolling regressions. We use a 36-month trailing window following BBW.

C. Performance Measures

We report four main statistical performance measures.[9] The first is "total R^2," or the fraction of variance in *contemporaneous* bond returns described by the common factors,

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - \hat{\beta}_{i,t}'\hat{f}_{t+1}\right)^2}{\sum_{i,t} r_{i,t+1}^2}. \tag{6}$$

This measure quantifies a model's success in describing the shared risks in bond returns. It aggregates over both assets (i) and time (t), and thus describes explained panel covariation. Most of our analysis focuses on out-of-sample

[8] Asvanunt and Richardson (2017) argue the DEF is poorly measured. A few preliminary observations support our decision to use our own market factor in place of DEF. First, our market factor is 74% correlated with DEF, verifying their qualitative similarity. Second, our market portfolio dominates DEF as a pricing factor in our sample, delivering a roughly 40% improvement in model fit compared to a model using DEF. We also verify that TERM has low explanatory power for corporate bond excess returns in our sample.

[9] We explain these in terms of individual bond returns $r_{i,t}$. Analogous measures are constructed for the managed portfolios $x_{l,t}$.

analysis, in which estimates of $\hat{\beta}_{i,t}$ are constructed using data only through date t. For IPCA, this uses $\hat{\beta}_{i,t} = z'_{i,t}\hat{\Gamma}_\beta$, where $\hat{\Gamma}_\beta$ is based on data through time t. The factor realization estimate $\hat{f}_{t+1}$ is constructed according to equation (2) from a combination of time $t+1$ realized returns and betas estimated through time t.[10] Note that the denominator is the sum of squared returns *without demeaning*. Gu, Kelly, and Xiu (2020) point out that out-of-sample comparison of fits against historical mean returns is flawed when it comes to analyzing single-name asset returns because the historical mean tends to severely underperform a naive forecast of zero, which unduly inflates the R^2. Benchmarking the R^2 against a mean of zero is a simple way to avoid this pitfall.

We also summarize IPCA model errors in terms of two commonly studied metrics in the cross-sectional asset pricing literature. Our second metric is the time-series R^2 for an individual test asset i, or $R_i^2 = 1 - \frac{\sum_t (r_{i,t+1} - \hat{\beta}'_{i,t}\hat{f}_{t+1})^2}{\sum_t r_{i,t+1}^2}$. For each set of portfolios that we analyze, we report the average time series R^2 among test assets. Because individual bonds differ in their number of nonmissing time-series observations (T_i), we report the weighted-average time-series R^2:

$$\text{Time Series } R^2 = \frac{1}{\sum_i T_i}\sum_i T_i R_i^2. \tag{7}$$

When the test assets are portfolios, all test assets have the same number of observations and (6) simplifies to the simple average time-series R^2 across assets.

The third metric is the R^2 from Fama-MacBeth cross-sectional regressions of test asset returns at time $t+1$ on (conditional) betas as of time t, $R_{t+1}^2 = 1 - \frac{\sum_i (r_{i,t+1} - \hat{\beta}'_{i,t}\hat{f}_{t+1})^2}{\sum_i r_{i,t+1}^2}$. We report the time-series average of cross-sectional regressions each period,

$$\text{Cross Section } R^2 = \frac{1}{T}\sum_t R_t^2. \tag{8}$$

Fama-MacBeth regressions quantify the cross-sectional predictive strength of asset-level signals. In the context of factor models, those signals are factor betas, and the cross-sectional fits assess the asset pricing restriction that betas predict returns.

When the betas correspond to a nontradedd factor, the cross-sectional regression also serves to estimate a slope coefficient, which has the interpretation of a factor-mimicking portfolio (whose time-series average is an estimate of the nontradedd factor's price of risk). For a model with traded factors (such as IPCA and the other models we compare against), it is most natural to calculate the cross section R^2 using the factor return itself as the slope estimate. We therefore define (8) to be the slope coefficient of the factor return itself, $\hat{f}_{t+1}$

[10] For observable factor models, this calculation replaces $\hat{f}_{t+1}$ with g_{t+1}.

for IPCA or g_{t+1} for observable factor models. It is problematic to reestimate cross-sectional regression slopes when the betas correspond to traded factors. Doing so can produce an inconsistency between the slope coefficient (i.e., the factor-mimicking portfolio) and the original factor that was tradable in the first place, and skews interpretation of a model's ability to fit the data.[11] This is an important point that we return to in our comparison of empirical models below.

Our fourth metric reports model fits in terms of pricing errors. Let $\alpha_i = \frac{1}{T_i}\sum_t (r_{i,t+1} - \hat{\beta}'_{i,t}\hat{f}_{t+1})$ be the average time-series error, or "pricing error," for the i^{th} test asset, and let $\bar{r}_i = \frac{1}{T_i}\sum_t r_{i,t+1}$ be the asset's time-series average excess return. We define the relative pricing error of a model as the sum of squared pricing errors divided by the sum of squared average returns,

$$\text{Relative Pricing Error} = \frac{\sum_i \alpha_i^2}{\sum_i \bar{r}_i^2}. \tag{9}$$

The three R^2 measures focus on the model's ability to explain realized return comovement among assets. In contrast, relative pricing error focuses on whether the model does a good job explaining differences in assets' average returns. Another contrast, of course, is that the framework represents a better asset pricing model when the relative pricing error value is lower.

In addition to the statistical measures above, we seek to understand what the model tells us about the stochastic discount factor in the corporate bond market. To that end, we calculate model-implied systematic bond portfolios. The first systematic bond strategy that we investigate is the tangency portfolio of IPCA factors. This represents the mean-variance efficient portfolio implied by the estimated IPCA model. We calculate the tangency portfolio on an out-of-sample basis, using an expanding history of IPCA factor returns to calculate the factors' covariance matrix and means. The second strategy sorts individual bonds into quintiles based on model-implied expected returns, $\hat{E}_t[r_{i,t+1}] = \hat{\beta}_{i,t}\hat{\lambda}$, where $\hat{E}_t[r_{i,t+1}]$ is constructed on a purely out-of-sample basis using estimates formed from data only up to date t.[12] The strategy is a zero-cost long-short portfolio taking an equal-weighted long position in bonds in the highest quintile of $\hat{E}_t[r_{i,t+1}]$ and a short position in the lowest quintile. We reconstitute portfolios each month based on the most recent model estimates.

II. Data

A. Returns

Our analyses use corporate bond returns from the Intercontinental Exchange (*ICE*). *ICE*, through its acquisition of Interactive Data Corporation,

[11] Likewise, to evaluate the price of risk of a traded factor, Fama-MacBeth regressions are redundant because the risk price can be evaluated simply based on the factor's time-series mean.

[12] Recall that $\hat{\beta}_{i,t}$ are linear combinations of the characteristics at time t coming from the parameter matrix $\hat{\Gamma}_\beta$, which we estimate only on data from t and before where $\hat{\lambda}$ is the average factor return estimated up to date t.

is considered the gold standard for corporate bond data and is the standard source used by banks, asset managers, and hedge funds. It underlies the Bank of America Merrill Lynch data used by Schaefer and Strebulaev (2008) and Israel, Palhares, and Richardson (2018).

The main alternative data source is Trade Reporting and Compliance Engine via Wharton Research Data Services (*WRDS/TRACE*). While several academic studies use *WRDS/TRACE* bond data, they have has a number of limitations relative to *ICE* data.[13] First, they present a shorter sample, starting in 2002. Also, the return sample size is comparatively small because one only observes *WRDS/TRACE* returns if trades happen sufficiently close to start and end dates of a return period. Second, *ICE* provides a number of complex bond analytics that are critical for accurately modeling bond returns, including hedge returns that strip out the pure interest rate (noncredit) component of bond returns, bond durations, and bond spread adjustments for option features such as callability (which are standard features of many corporate bonds and create large distortions in bond spreads and returns). *WRDS/TRACE* does not provide these analytics, so the researcher must perform crude versions of these adjustments manually. In contrast, *ICE* performs these calculations as part of its platform, using proprietary methods and additional information sources, which is one of the main reasons why sophisticated practitioners use *ICE* data.

Our main data set starts in December of 1999 and ends in December 2020, which includes the period of unprecedented corporate bond market turmoil induced by the COVID-19 pandemic. To build our corporate bond universe, we work from the set of bonds belonging to the Bank of America High Yield (H0A0) and Investment Grade (C0A0) Indices.

The bond total return is defined as the price change plus distributions (coupons) divided by initial price. We focus in our analysis on monthly returns. The credit excess return is the total return minus a hedging portfolio of Treasuries. The hedging portfolio is built such that if there is a small move on the risk-free curve, the hedge portfolio offsets the response in the risky bond's price. Note that this is a more precise version of picking a Treasury of similar maturity to hedge each bond.[14]

Corporate bond returns can have vastly different levels of risk depending on the credit quality of the issuer and the macroeconomic environment. To ensure that factor model estimates are not driven by only the most volatile segments of the sample, we adjust bond returns to have similar ex ante volatility. We scale returns by the previous month's "Duration times Spread" (*DtS*) following Ben Dor et al. (2007) who derive *DtS* as an analytical, accurate, and forward-

[13] A companion working paper Kelly and Pruitt (2022) reruns the present paper's core analysis using publicly-available data from *WRDS/TRACE* and finds that the key conclusions continue to hold. The companion paper further analyzes important differences in the *WRDS/TRACE* returns, which is beyond the scope of the present paper.

[14] Hedging with a maturity-matched Treasury, though commonly used, has many shortcomings, such as the Treasury having different curve exposure because of a likely different coupon profile and not reflecting the option the bond issuer has to call its bond, a very common feature (especially among high-yield issues).

looking approximation of bond return volatility. In particular, we define

$$r_{i,t+1} = \frac{\tilde{r}_{i,t+1}}{\max\left(DtS_{i,t}, \underline{DtS}\right)}, \tag{10}$$

where $\tilde{r}_{i,t+1}$ is the raw excess credit return, $DtS \equiv \text{duration}_{i,t} \times \text{spread}_{i,t}$, and $\underline{DtS}$ is set at 0.25.[15] Forty percent of bonds have a DtS less than $\underline{DtS}$, and therefore these low-volatility bonds are essentially unadjusted (as they are all divided by the same number). This highlights that the role of DtS scaling is to downweight *high*-volatility bonds that unduly affect least-squares estimation. The return transformation in (10) is designed to reduce the degree of heteroskedasticity in corporate bond returns, which helps improve the stability of estimated models as well as reduce the leverage of economically unimportant bonds trading at a few cents on the dollar.[16]

In addition to the characteristic-managed portfolios (x_t) above, we also study two additional sets of portfolios as test assets following BBW. The first are 25 size/maturity-sorted portfolios. For these, we two-way sort bonds into quintile bins (independently) based on total outstanding bond face value and bond maturity. We then value-weight the bonds (using bond face value) to build portfolio returns. The second set of portfolios are value-weighted industry portfolios following the Fama and French (1997) 30-industry classification. When building these, we require that an industry has at least 500 total bond-month observations to be included, and that an industry-month is nonmissing if it has at least ten bonds present—these requirements leave us with 28 industry portfolios.

B. Characteristics

Our corporate bond data contain bond analytics such as spread duration, option-adjusted spread, and credit excess return (bond total return in excess of a duration-matched interest rate hedge). The data also include bond contract attributes such as maturity, coupon, total face value of issue, and price. In addition to these characteristics, we survey the credit literature for a list of candidate "anomaly" characteristics to serve as IPCA instruments. We then narrow the list down to ensure high data coverage going back in time. We ultimately settle on 29 bond/firm characteristics. The characteristics are listed in Appendix Table AI along with references to their use in prior literature.

We discard bond-month observations with extreme bond spreads (less than 50 bps or greater than 2,000 bps at the beginning of the period). We also discard

[15] In our data, DtS has a mean of 0.529, a median of 0.35, a minimum of 0.003, and a maximum of 8.9.

[16] The Internet Appendix shows that scaling by DtS results in a more homogeneous cross-sectional distribution of corporate bond returns. An alternative is to scale bond returns by an estimate of bond return volatility. This accomplishes the same homogenization of bond returns, but comes at the cost of being backward-looking. In robustness analyses below, we show that scaling returns by historical volatility produces similar results as our main analysis. The Internet Appendix may be found in the online version of this article.

Table I
Characteristic-Managed Portfolio Performance

This table presents annualized Sharpe ratios of characteristic-managed portfolios (x_t). * and *** denote significance at the 5% level and 1% level, respectively, based on t-statistics from Lo (2002). Table AI describes the characteristics.

Characteristic	Sharpe	Characteristic	Sharpe
Bond age	0.34	Market leverage	−0.82**
Coupon	0.47*	Turnover volatility	0.49*
Face value	−0.61**	Spread	0.81**
Book-to-price	−1.03**	Operating leverage	0.41
Debt-to-EBITDA	−0.42	Profitability	0.14
Duration	−0.97**	Profitability change	0.60**
Mom. 6m equity	1.76**	Rating	0.53*
Earnings-to-price	−0.72**	Distance-to-default	0.54*
Equity market cap.	−0.32	Bond skewness	−0.67**
Equity volatility	−0.19	Mom. 6m log(Spread)	−0.80**
Firm total debt	−0.46*	Spread-to-D2D	1.25**
Mom. 6m	−0.84**	Bond volatility	−0.49*
Mom. 6m industry	0.24	Value-at-risk	0.07
Mom. 6m × ratings	−0.47*	VIX beta	0.30
Book leverage	−0.26		

bonds with duration less than 0.25 years. Our estimator requires bond-month observations with no missing characteristic values. Bonds with missing data can still appear in our sample, but only for months in which their characteristic data are available. This results in 14,600 unique bonds over the 264 months in our sample period, for a total of 555,894 bond-month observations.

Each month, we cross-sectionally rank, demean, and scale the characteristics (except the constant) to the $[-0.5, 0.5]$ interval, following KPS. This places characteristics on the same scale, thus Γ_β estimates are directly comparable across characteristics, and controls outliers. Taken together, we use 30 instruments in $z_{i,t}$ to understand bond-level factor exposures.

C. Motivating Evidence for IPCA

Table I reports the investment performance of the managed portfolio $x_{l,t}$ for each characteristic $l = 1, \ldots, L$. The sign of reported average returns indicates the direction of the strategy. For example, the duration portfolio earns an annualized Sharpe ratio of -0.97, meaning that it is profitable to buy short-duration bonds and sell long-duration bonds. Coupon, face value, book-to-price, duration, equity momentum, earnings-to-price, total debt, bond return momentum (by itself and interacted with ratings), market leverage, turnover volatility, spread, profitability change, rating, distance-to-default, bond skewness, spread momentum, spread-to-D2D, and bond volatility all earn statistically significant Sharpe ratios at the 5% level.

The signs of some characteristic patterns may appear unexpected, but they generally align with results in prior literature. For example, the negative return of the duration portfolio is consistent with the low-risk anomaly reported for both corporate credit and government bonds in Frazzini and Pedersen (2014). Likewise, the negative returns of volatility-sorted portfolios are consistent with the low-volatility puzzle documented by Ang et al. (2006) in equities. Negative returns on book leverage and market leverage are consistent with the distress risk puzzle of Campbell, Hilscher, and Szilagyi (2008) in equities.[17] Value portfolios (book-to-price and earnings-to-price) also have negative average returns, while Choi and Kim (2018) find a positive sign for book-to-price. The difference is likely explained by the difference in our sample. The Choi and Kim (2018) sample includes the 1990s and ends in 2012, a period that was particularly strong for the value strategy. In contrast, more than half of our sample consists of post-2010 data, a sample that has yielded negative value returns on average in many asset classes.[18] Finally, we note that the signs of all characteristic portfolios are the same whether we use *DtS*-scaled returns (Table I) or unscaled returns (in the Internet Appendix) with the exception of: equity volatility, profitability, and VIX beta (which are insignificant in either case); and duration and bond volatility (which become insignificant in unscaled returns).

Overall, Table I provides preliminary evidence that many of the characteristics we study are useful predictors of excess bond returns. Beyond just return prediction, however, we seek a model that also explains bonds' covariances with nondiversifiable sources of risk. To this end, we investigate the extent to which bond characteristics predict a bond's beta on common risk factors. We do so via the regression

$$RB_{i,t+1} = b_1' z_{i,t} + \text{constant} + \text{error}, \tag{11}$$

where $z_{i,t}$ is a vector of instruments and $RB_{i,t+1}$ measures the future realized beta between bond i and the bond market factor (equal-weighted average of bond returns in our sample). In a similar analysis for equities, Kelly, Moskowitz, and Pruitt (2021) use daily stock returns during one month ($t+1$) or several months ($t+1$ to $t+12$) to calculate realized betas. But daily bond returns are much noisier due to their broad illiquidity over short horizons, hence we instead calculate the realized beta from monthly return data. Specifically, $RB_{i,t+1}$ is the coefficient from regressing bond i's excess return on the market factor using data for months $t+1$ to $t+12$.

Table II shows that the 29 bond characteristics predict future 12-month betas on the market with a panel R^2 of 17%. This is an impressive degree of predictability given the noisiness of betas, each of which is estimated from

[17] Leverage is an endogenous equilibrium outcome and more creditworthy firms often take on a larger debt burden, which is the likely driver of the negative average return for leverage portfolios.

[18] Another aspect of the data that likely contributes to the difference in value results between our paper and Choi and Kim (2018) is that we hedge interest rates in our bond return construction, while Choi and Kim (2018) do not.

Table II

Characteristics Predict Bond Market Beta

This table presents estimated coefficients from a panel predictive multiple regression of realized bond-market beta *RB* on the characteristics. Standard errors are clustered by firm and month, with ** denoting significance at the 5% level and ** denoting significance at the 1% level.

Characteristic	Coeff.	Characteristic	Coeff.
Bond age	−0.49**	Market leverage	−0.24**
Coupon	0.06	Turnover volatility	0.13**
Face value	0.37**	Spread	0.26**
Book-to-price	−0.12**	Operating leverage	−0.12**
Debt-to-EBITDA	−0.06	Profitability	−0.09**
Duration	0.04	Profitability change	−0.03
Mom. 6m equity	−0.03	Rating	0.27**
Earnings-to-price	−0.07**	Distance-to-default	−0.37**
Equity market cap.	−0.28**	Bond skewness	0.01
Equity volatility	0.06	Mom. 6m log(Spread)	0.31**
Firm total debt	0.48**	Spread-to-D2D	−0.13**
Mom. 6m	−0.50**	Bond volatility	−0.09
Mom. 6m industry	−0.05*	Value-at-risk	−0.09**
Mom. 6m × ratings	0.20*	VIX beta	−0.58**
Book leverage	−0.06	Constant	1.1076**
Number of observations = 391,049			
$R^2 = 16.62\%$			

only 12 observations. The classical measurement error in $RB_{i,t+1}$ biases the R^2 downward (but does not bias the regression coefficient estimates as beta estimation errors are uncorrelated with the lagged characteristics $z_{i,t}$). The F-test of this regression has a p-value of approximately zero. Several of the bond characteristics are individually significant predictors of a bond's future beta. The strongest predictors are lags of bond age, face value, total debt, bond momentum, distance-to-default, spread momentum, and VIX beta, all of which have significant coefficients that are larger than 0.3 in magnitude (coefficient magnitudes are comparable across regressors, which all use the same rank-standardized scale).

Taken together, the results of Tables I and II suggest that bond characteristics predict both the risk and the returns of bonds. The specifications underlying these analyses are ad hoc, however. Table I documents return predictability but does not shed light on whether this predictability operates through mispricing or through the risk-return trade-off. Table II shows that these characteristics also predict bond riskiness, but the degree of alignment with Table I is unclear.

The IPCA model unifies these two lines of inquiry. It allows characteristics to predict future covariances with common risk factors but does not require the researcher to take a stand on the specific sources of risk ex ante. Our preliminary covariance analysis is restricted to one prespecified factor that is unlikely to capture the full gamut of risks that bondholders face. Instead, IPCA relies on the data to identify and estimate the most plausible latent

Table III
IPCA In-Sample Performance

This table presents in-sample total, time-series, and cross-section R^2s, and relative pricing errors in percentages for the IPCA model restricted to have no intercepts. The sample is January 1999 through December 2020. Panel A reports results for individual corporate bond returns and Panel B reports results for characteristic-managed portfolios.

	K				
	1	2	3	4	5
Panel A: Individual Bonds (r_t)					
Total R^2	41.6	45.0	46.9	48.6	49.7
Time-Series R^2	33.4	36.5	39.4	42.2	43.1
Cross-Section R^2	23.1	25.8	28.3	32.0	33.3
Relative Pricing Error	53.6	77.4	65.4	59.4	60.4
Panel B: Managed Portfolios (x_t)					
Total R^2	93.4	95.8	97.9	98.6	99.2
Time-Series R^2	30.3	54.9	73.6	81.5	88.0
Cross-Section R^2	74.1	77.0	86.6	92.1	94.4
Relative Pricing Error	32.1	33.3	34.3	1.5	0.3

risk factors. Moreover, IPCA allows the researcher to determine whether characteristics predict future bond returns due to time-varying factor betas in line with a risk-return trade-off (i.e., through a risk compensation channel) or whether they proxy for alpha above and beyond factor risk (i.e., through a bond mispricing channel). If we find no alpha versus the model that would suggest characteristics predict future returns because they capture factor covariance. We pursue this investigation in the next section.

III. Empirical Results

In this section, we provide our main empirical results, compare our model to existing models, and provide a battery of robustness checks. Further analysis based on unscaled returns data is in the Appendix and results for individual market segments are presented in the Internet Appendix.

A. In-Sample and Out-of-Sample Fits

Table III reports in-sample model fits using the entire data set. With a single factor, the zero-alpha IPCA model explains 41.6% of the total variation in individual bond returns (Panel A). As reference points, the total R^2 in the one-factor IPCA specification for monthly individual stock returns is 15% in KPS, and a one-factor model using just the equal-weight bond market return has an in-sample total R^2 of 41% (discussed more in Table VI). The average time-series R^2 is 33.4% and the cross-section R^2 is 23.1%. The relative pricing error

Table IV

IPCA Out-of-Sample Performance

This table presents out-of-sample total, time-series, and cross-section R^2s and relative pricing errors in percentages for the IPCA model restricted to have no intercepts. The sample is January 1999 through December 2020. The first out-of-sample test observation is 36 months after the start of our sample. Panel A reports results for individual corporate bonds returns and Panel B reports results for characteristic-managed portfolios.

	K				
	1	2	3	4	5
Panel A: Individual Bonds (r_t)					
Total R^2	40.9	43.8	45.3	48.6	50.7
Time-Series R^2	35.2	37.6	39.5	42.3	44.6
Cross-Section R^2	25.3	27.8	29.8	32.3	34.0
Relative Pricing Error	52.7	55.5	53.6	60.3	63.4
Panel B: Managed Portfolios (x_t)					
Total R^2	90.7	93.2	94.4	97.2	98.5
Time-Series R^2	8.0	31.5	42.8	66.3	79.0
Cross-Section R^2	76.0	80.8	86.3	90.6	93.6
Relative Pricing Error	26.0	17.7	14.7	2.8	1.8

is 53.6% among individual bonds. At the managed portfolio level (Panel B), the one-factor total R^2 is 93.4% (compared to 89.1% for the bond market model in Table VI) and the pricing error is 32.1%.

In the Appendix, we describe and estimate an alpha-based asset pricing test for the IPCA model recommended by KPS. When $K = 1$, the test indicates that allowing for an alpha significantly improves model fit and easily rejects the zero-alpha null with a p-value near zero (Table BI). However, increasing the number of IPCA factors leads to large improvements in model fit and reduces pricing errors. With $K = 5$, the relative pricing error at the portfolio level reaches as low as 0.3%, meaning that the model nearly perfectly explains differences in average returns across portfolios; total, time-series, and cross-section R^2 metrics for realized returns reach 88% or better for test portfolios; and, we fail to reject the null of zero alpha at the 1% level in Table BI. In other words, when the factor space is sufficiently rich, the statistical test finds that cross-sectional differences in average returns are better explained by factor risk. These results support a five-factor zero-alpha IPCA specification, which we use as our main IPCA bond model hereafter.

In Table IV, we report model fits on an out-of-sample basis. We use an expanding estimation window from time 1 to t to estimate Γ_β, which delivers estimates of each $\beta_{i,t}$. The factor realization at time $t + 1$ is recovered from a cross-section regression of returns at $t + 1$ on betas estimated through time t,

Table V
Comparative Out-of-Sample Performance

This table presents out-of-sample total, time-series, and cross-section R^2s and relative pricing errors in percentages for the IPCA model restricted to have no intercepts. The sample is July 2004 through December 2019 (to accommodate the shorter BBW data).

	MKT	BBW	FF	IPCA
Panel A: Total R^2				
Individual Bonds (r_t)	32.2	−16.9	−3.5	45.4
Managed Portfolios (x_t)	87.5	−5.6	25.5	97.7
Size/Maturity Portfolios	90.6	−1.9	27.8	96.3
Industry Portfolios	87.6	0.1	29.0	92.0
Panel B: Time-Series R^2				
Individual Bonds (r_t)	34.6	−10.4	−8.0	43.8
Managed Portfolios (x_t)	−7.7	−49.5	−26.9	79.1
Size/Maturity Portfolios	91.7	−3.3	27.6	96.5
Industry Portfolios	88.1	0.7	29.3	92.4
Panel C: Cross-Section R^2				
Individual Bonds (r_t)	23.3	−11.7	−20.4	35.0
Managed Portfolios (x_t)	78.2	−115.0	−134.7	96.6
Size/Maturity Portfolios	80.2	−113.3	−140.2	88.4
Industry Portfolios	68.8	−78.3	−119.2	77.2
Panel D: Relative Pricing Error				
Individual Bonds (r_t)	68.1	100.1	75.8	38.9
Managed Portfolios (x_t)	26.3	105.8	37.6	2.9
Size/Maturity Portfolios	12.8	141.6	27.5	1.7
Industry Portfolios	13.6	278.2	11.1	8.0
Panel E: Reestimated Cross-Section R^2				
Individual Bonds (r_t)	28.3	29.5	30.2	35.0
Managed Portfolios (x_t)	79.3	88.8	91.1	96.6
Size/Maturity Portfolios	88.1	91.7	92.2	88.4
Industry Portfolios	76.3	81.1	81.4	77.2

per equation (2).[19] The first out-of-sample test observation is 36 months after the start of our sample.

The main takeaway from Table IV is a striking consistency between in-sample and out-of-sample performance of the IPCA model. With five factors and zero alpha, the IPCA conditional bond model achieves a total R^2 of 50.7% and 98.5% for individual bonds and managed portfolios, respectively. The

[19] This is the IPCA equivalent of out-of-sample Fama-MacBeth regression.

time-series and cross-section R^2 are also very close to the in-sample estimates. Moreover, relative pricing errors remain impressive, at 63.4% for individual bonds and only 1.8% for managed portfolios.

This high degree of stability between in-sample and out-of-sample performance is rationalized by the comparatively small parameterization of IPCA. The number of parameters in the beta specification is $L \times K$, or 150 for the five-factor model. By contrast, an observable-factor model with static regression betas requires $N \times K$ parameters, which in our sample for a five-factor model requires roughly 70,000 parameters.

B. Model Comparison

Next, we compare our zero-alpha five-factor IPCA specification to other models in the literature. We estimate the competing observable factor models according to equation (5). We follow BBW and reestimate betas each month using the most recent 36 months of data. From the estimated betas and the observable factors, the out-of-sample total R^2, time-series R^2, and relative pricing errors can be computed directly. We do this for individual bonds and characteristic-managed portfolios, as well as for size/maturity-sorted portfolios and industry portfolios as in BBW. For comparability across models, Tables V and VI restrict analysis to the set of observations for which estimates from all models are available, July 2004 to December 2019. The results for IPCA therefore differ slightly from those reported in Tables IV and III, which use data from 1999 to 2020. The corporate bond market experienced unusually high volatility in 2020 induced by the COVID-19 pandemic, so the exclusion of 2020 from Tables V and VI leads to a reduction in pricing errors for all models.

Table V compares the out-of-sample performance of observable factor models with static betas. In general, only the market model is reasonably competitive with IPCA on an out-of-sample basis. It delivers large positive total, time-series, and cross-section R^2, and it generally delivers small pricing errors. While the market model fits well across the board, it remains dominated by the IPCA model along all dimensions. The most notable difference is in pricing errors. Among individual bonds, market model relative pricing errors are 68.1%, versus 38.9% for IPCA. For characteristic-managed portfolios, the difference in pricing errors is more stark at 26.3% for the market model versus only 2.9% for IPCA.

BBW is less competitive, with negative out-of-sample total, time-series, and cross-section R^2, indicating that out-of-sample exposures to the BBW factors do a worse job fitting the bond data than a naïve model that sets all fitted bond returns to zero. The relative pricing errors are greater than 100%, again indicating that BBW underperform a naïve model of zero average returns for all test assets. The failure to fit out-of-sample bond returns also afflicts the FF model, though less severely.

What explains the poor performance of observable multifactor models, and how does this reconcile with the results in BBW? The first answer is parameter

Table VI
Comparative In-Sample Performance

This table presents in-sample total, time-series, and cross-section R^2s and relative pricing errors in percentages for the IPCA model restricted to have no intercepts. The sample is July 2004 through December 2019 (to accommodate the shorter BBW data).

	MKT	BBW	FF	IPCA
Panel A: Total R^2				
Individual Bonds (r_t)	41.0	26.8	30.0	47.8
Managed Portfolios (x_t)	89.1	35.2	43.4	99.3
Size/Maturity Portfolios	92.5	37.5	44.9	97.3
Industry Portfolios	88.9	37.2	44.2	92.6
Panel B: Time-Series R^2				
Individual Bonds (r_t)	41.0	23.9	26.8	46.6
Managed Portfolios (x_t)	11.8	14.0	9.6	92.0
Size/Maturity Portfolios	93.2	36.8	45.0	97.3
Industry Portfolios	89.3	37.3	44.4	92.9
Panel C: Cross-Section R^2				
Individual Bonds (r_t)	26.2	11.8	14.6	35.2
Managed Portfolios (x_t)	75.1	−72.2	−86.1	95.6
Size/Maturity Portfolios	77.9	−71.1	−102.4	86.1
Industry Portfolios	65.9	−38.4	−56.5	73.8
Panel D: Relative Pricing Error				
Individual Bonds (r_t)	61.4	81.2	74.8	45.9
Managed Portfolios (x_t)	23.6	27.2	26.9	0.1
Size/Maturity Portfolios	6.1	16.0	10.2	0.9
Industry Portfolios	8.8	26.1	4.7	4.0
Panel E: Reestimated Cross-Section R^2				
Individual Bonds (r_t)	28.5	32.8	34.4	35.2
Managed Portfolios (x_t)	76.1	84.3	90.3	95.6
Size/Maturity Portfolios	85.5	90.0	89.8	86.1
Industry Portfolios	72.6	77.9	79.1	73.8

instability. In Table VI, we report in-sample fits, where we see that results for our implementation of the BBW model align much more closely with the fits originally reported by BBW. For observable factor models, the only difference between Tables V and VI is that in-sample fits use betas from the full time series asset-by-asset while out-of-sample fits use rolling out-of-sample betas. The fact that the BBW total and time-series R^2 become negative out-of-sample is thus due to the fact that their past betas do not align well with future betas. This is also true, but to a lesser extent, for the FF model.

The second point necessary to reconcile our results with those in BBW relates to how cross-sectional fits are assessed. Because the observable factor models use traded factors, the cross-section R^2 is immediately available from the beta estimates and realized factor returns.[20] If the factors are traded, their returns are the appropriate slopes for assessing the cross-sectional association between returns and betas. Reestimating the cross-section regression has the awkward implication that the factor-mimicking portfolio and the *already traded factor that is being mimicked* are allowed to diverge. To highlight this effect, we report two versions of the cross-section R^2. The first imposes the model restriction that traded factor returns equal the cross-section slope (i.e., without reestimation). This R^2 is shown in Panel C of Table V (and is negative for all test assets based on the BBW model). In Panel E of Table V, we report the R^2 from failing to impose the model restriction. A side effect of reestimating the cross-sectional regression slope is that the R^2 gives an inflated view of the model's cross-sectional fit, and these results look far better for BBW. In fact, the discrepancy between the R^2 in Panels C and E is itself an indicator of model misspecification.

Figure 1 graphically illustrates out-of-sample pricing errors. For each model, we draw a scatterplot of average test asset returns (including characteristic-managed portfolios, size/maturity-sorted portfolios, and industry portfolios) versus average out-of-sample predictions from the model. For comparability, we normalize all portfolios to have 10% annualized volatility. For the market model, BBW, and FF, many significant pricing errors manifest as a cluster around the horizontal axis. In contrast, the IPCA model (with $K = 5$) produces a scatter that closely aligns with the 45° line, demonstrating small out-of-sample pricing errors for a wide range of test portfolios.

It is worth reiterating the drastic differences in the number of estimated parameters for each model. To model individual bonds, observable factor models rely on vastly more parameters than IPCA because they independently estimate regression betas for each asset. The number of parameters in an observable factor model is thus equal to the number of factors times the number of assets, or roughly 14,000 for the market model and upward of 70,000 for the FF model. The power of IPCA comes in large part from the parsimony it imposes on betas by estimating them jointly as a function of observable asset characteristics. For the five-factor IPCA model, we estimate 1,470 parameters, 150 of which constitute Γ_β, and the remaining $5 \times 264 = 1{,}320$ are the estimated realizations of five factors each month, that is 98% fewer parameters than a traditional five-factor model.[21]

While the parameter requirements of observable factor models are less severe when the test assets are portfolios, this parameter reduction is somewhat misleading. To implement an observable factor model, the researcher must make a difficult and ambiguous choice about which test assets to use and must

[20] After estimating time-series betas, BBW run additional cross-section regressions of bond returns on betas. This choice fails to impose an asset pricing restriction imposed by the factor model.

[21] These parameter counts are for in-sample implementation of each method.

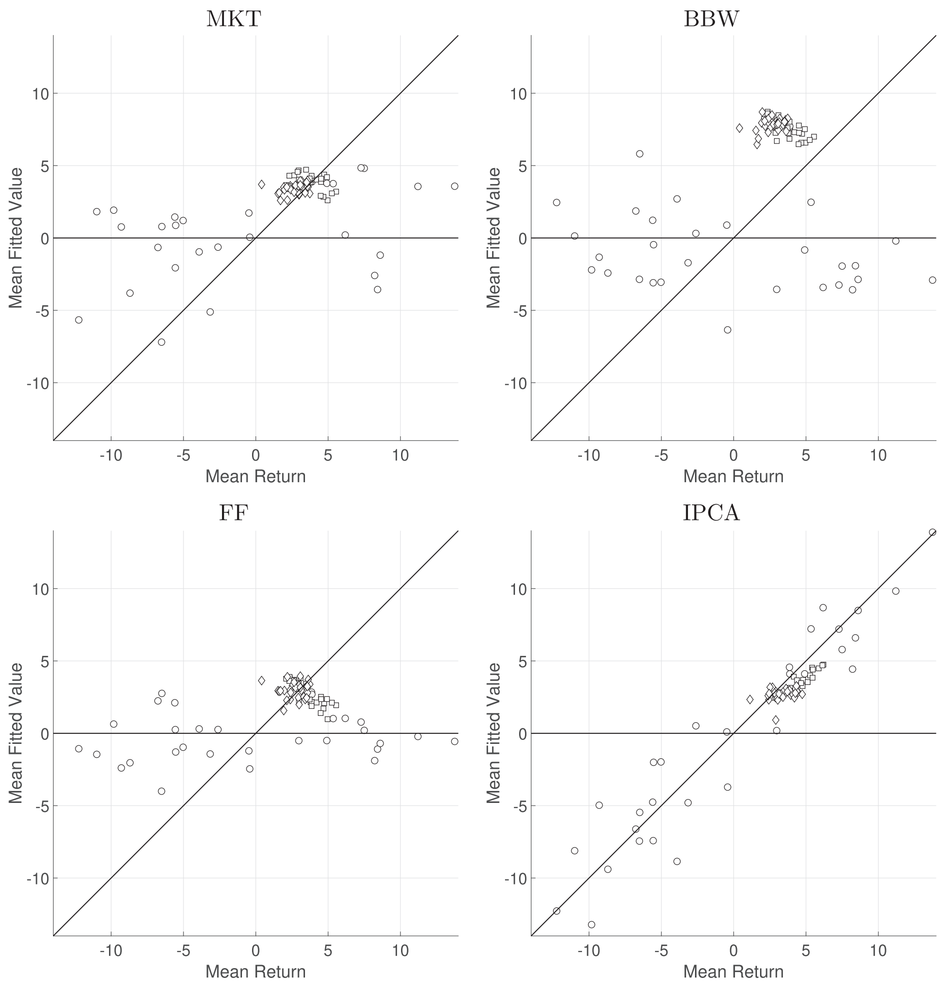

Figure 1. Average returns versus out-of-sample average fitted values. The figure shows annualized percentage average returns for portfolios (scaled to have 10% annual volatility) on the horizontal axis and average out-of-sample predictions from each model on the vertical axis. The 45° line is shown in black. Circles represent characteristic-managed portfolios (x_t), squares are size/maturity-sorted portfolios, and diamonds are industry portfolios.

reestimate parameters for each set of test assets. IPCA, on the other hand, uses the exact same model parameters regardless of whether the model is evaluated in terms of single-name bond returns (r_t) or bond portfolios (x_t), providing a coherent model of both at the same time. It is important to keep this in mind when comparing across sets of test assets in Table V—the estimated observable factor models change row-by-row, but the IPCA model does not. Instead, IPCA's individual-bond fits have been aggregated into the portfolios being reported with internal consistency of IPCA's estimates for all test assets.

Table VII

IPCA Investment Strategy Performance

This table presents out-of-sample annualized Sharpe ratios for the restricted ($\Gamma_\alpha = \mathbf{0}$) model.

	K				
	1	2	3	4	5
Tangency	0.10	1.19	2.58	6.08	6.23
Spread	0.30	1.35	2.39	3.76	3.53

C. IPCA and Systematic Bond Strategies

Next, we explore our model's implications for the mean-variance efficient frontier of corporate bonds. We study out-of-sample performance of two systematic bond investment strategies implied by our estimates for the five-factor IPCA model. Because our model enforces zero intercepts, their implied strategies are interpreted as exploiting predicted compensation for exposure to aggregate risks.

Table VII describes the out-of-sample performance of IPCA systematic bond strategies for models with $K = 1, \ldots, 5$. In the case of the factor tangency portfolio, the Sharpe ratio is 0.10 for $K = 1$ and rises monotonically with K reaching 6.23 for the five-factor model. The pattern is similar for the spread strategy, whose Sharpe ratio starts at 0.30 and rises to 3.53.[22] For $K > 1$, Sharpe ratios for both strategies are statistically significant at the 1% level. As a reference point, the annualized Sharpe ratio of an equal-weighted portfolio of all bonds in our sample is 0.26, and Table I shows that three of the characteristic-managed portfolios produce Sharpe ratios in excess of 1.0 (in absolute value). Another useful benchmark is the investment strategy proposed by Israel, Palhares, and Richardson (2018), who combine defensive, momentum, carry, and value signals to produce a corporate bond portfolio earning a Sharpe ratio of 2.2. As a last comparison, KPS find that a five-factor IPCA strategy among U.S. stocks earns an annual out-of-sample Sharpe ratio of 3.9.

Trading in the corporate bond market is well known to be costly due to its microstructure nuances and general illiquidity (for a survey, see Bessembinder, Spatt, and Venkataraman (2020), and references therein). We report strategy performance accounting for trading costs in Table VIII. We use trading cost estimates from Choi and Huh (2019) who recommend a one-way cost of 17 bps for investment grade bonds and 19 bps for high yield. To be conservative, we apply a one-way cost of 19 bps to all trades. We follow Bredendiek, Ottonello, and Valkanov (2019) to calculate portfolio net returns as

$$r_{p,t+1} = \sum_i w_{i,t} r_{i,t+1} - 19 \text{ bps} \times \sum_i |w_{i,t} - w_{i,t-1}|, \tag{12}$$

[22] The Internet Appendix Table reports additional statistics of the quintile sort portfolios for the $K = 5$ model.

Table VIII

IPCA Investment Strategy Net Performance

This table presents out-of-sample turnover, gross Sharpe ratios, and net Sharpe ratios for systematic bond strategies based on the $K = 5$ IPCA model. We assume one-way trading costs of 19 bps. γ controls the extent of exponential smoothing applied to optimal portfolio weights.

	Turnover		Gross Sharpe Ratio		Net Sharpe Ratio	
γ	Tangency	Spread	Tangency	Spread	Tangency	Spread
0.0	0.68	0.76	6.23	3.53	2.48	1.37
0.1	0.62	0.71	6.19	3.49	2.69	1.42
0.2	0.57	0.65	6.08	3.42	2.85	1.46
0.3	0.52	0.60	5.89	3.32	2.93	1.47
0.4	0.48	0.55	5.60	3.19	2.93	1.47
0.5	0.43	0.49	5.17	3.00	2.84	1.44
0.6	0.38	0.44	4.60	2.75	2.64	1.38
0.7	0.33	0.37	3.88	2.41	2.33	1.28
0.8	0.27	0.30	3.04	1.94	1.92	1.10
0.9	0.20	0.21	2.05	1.29	1.37	0.79

where $w_{i,t}$ is the model-recommended weight in asset i at time t.[23] Along with this net return calculation, we also compute a turnover statistic that describes the fraction of the portfolio that turns over each month on average:

$$\text{Turnover} = \frac{1}{T}\sum_t \frac{\sum_i |w_{i,t} - w_{i,t-1}|}{\sum_i |w_{i,t-1}|}. \tag{13}$$

The first row of Table VIII shows that the monthly turnover of our systematic strategies is around 70%. After accounting for trading costs, the net Sharpe ratio is 2.48 for the tangency portfolio and 1.37 for the spread portfolio.

Consideration of trading costs is important for understanding the real-world practicality of a research-based strategy. However, our model is optimized without regard for trading costs, and thus a trading cost adjustment may understate the strategy's potential. Cost-aware implementation of a strategy naturally leads to a modified portfolio that updates positions more gradually than the cost-agnostic model estimated above. In the remaining rows of Table VIII, we study the performance of IPCA systematic bond strategies when weights are "slowed down" by exponential smoothing. In particular, we move from the raw model-based weights w_t to the smoothed weights $\tilde{w}_t$ according to

$$\tilde{w}_t = (1-\gamma)w_t + \gamma\tilde{w}_{t-1} \tag{14}$$

and initialize with $\tilde{w}_0 = w_1$. Increasing γ decreases the turnover of the strategy, which degrades the signal and therefore lowers the gross Sharpe ratio. The

[23] The Internet Appendix Table reports net portfolio performance for one-way costs ranging from 10 to 40 bps following Bredendiek, Ottonello, and Valkanov (2019) and Bessembinder et al. (2018).

Table IX

Testing Individual Characteristics

This table presents the importance of each individual characteristic l measured as the square root of the sum of squared elements in the row l^{th} row of Γ_β. * and ** denote significance at the 5% and 1% level based on bootstrapped characteristic significance tests.

Characteristic	Impact	Characteristic	Impact
Bond age	0.15^{**}	Market leverage	0.13
Coupon	0.11^{*}	Turnover volatility	0.05
Face value	0.11^{**}	Spread	0.34^{**}
Book-to-price	0.11	Operating leverage	0.09
Debt-to-EBITDA	0.13^{*}	Profitability	0.11
Duration	0.32^{**}	Profitability change	0.03
Mom. 6m equity	0.25^{**}	Rating	0.24
Earnings-to-price	0.06	Distance-to-default	0.17
Equity market cap.	0.24^{*}	Bond skewness	0.05
Equity volatility	0.13^{*}	Mom. 6m log(Spread)	0.13
Firm total debt	0.17^{*}	Spread-to-D2D	0.23^{*}
Mom. 6m	0.17	Bond volatility	0.31^{**}
Mom. 6m industry	0.13^{**}	Value-at-risk	0.06
Mom. 6m $\times$ ratings	0.15	VIX beta	0.23^{*}
Book leverage	0.07	Constant	0.34^{**}

benefit of reduced turnover is that fewer trading costs are incurred, which improves the net Sharpe ratio all else equal. Table VIII shows that this trade-off is optimized around $\gamma = 0.3$, in which case the net Sharpe ratio is 2.93 for the tangency portfolio and 1.47 for the spread portfolio. In summary, IPCA-based systematic bond strategies generate attractive investment performance after accounting for reasonable implementation costs.[24]

D. Characteristics and Factors

By understanding the extent to which different bond characteristics affect the IPCA model, we can interpret the model's estimated factors. This is accomplished most directly by inspecting the Γ_β matrix. The l^{th} row of Γ_β describes how characteristic l influences a bond's beta on each of the K factors. We measure and test the overall model contribution of each characteristic l (while simultaneously controlling for all other characteristics) by calculating the sum of squared elements of the l^{th} row of Γ_β. KPS propose a Wald-test statistic based on this quantity and develop a bootstrap procedure to construct p-values. Table IX reports this square root of this sum, with ** and * indicating

[24] In the Internet Appendix, we take a different approach to slowing down turnover. We restrict the set of characteristics to those whose average time-series volatility is no larger than that of the duration characteristic. Nineteen characteristics survive this filter (listed in the table notes), which reduces turnover by about 40 percentage points. The resulting tangency strategy and spread strategy net Sharpe ratios are 1.90 and 1.57, respectively, without relying on additional weight smoothing. We thank our referee for this suggestion.

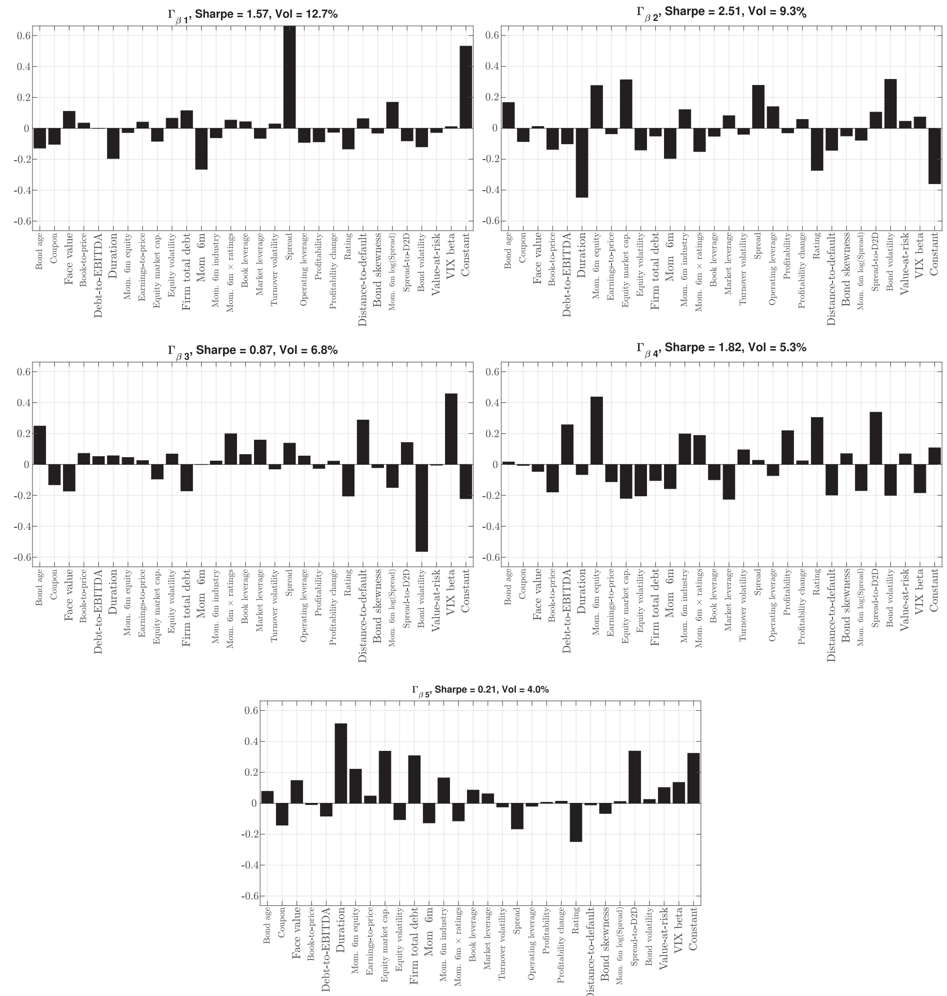

Figure 2. Γ_β **estimates**. The figure shows estimated Γ_β coefficients. Each panel corresponds to a different column of Γ_β, which in turn correspond to each of the five IPCA factors. The model's identification conditions ensure that each column norm equals one and that columns are orthogonal.

that a characteristic significantly contributes to the model at the 1% and 5% level, respectively. Because all of the characteristics are cross-sectionally rank standardized, the reported magnitudes are directly comparable across characteristics. We find that of the 30 characteristics we study, 15 are significant contributors to the model at the 5% level or better.

Four characteristics stand out in terms of the magnitude of their impact: spread, duration, bond volatility, and the constant. Figure 2 plots the columns of the estimated Γ_β matrix, which provides a further means of interpreting the estimated factors.[25] As noted earlier, due to its latent factor specification, the IPCA factors are identified only up to a rotation. Our identifying normalization imposes that the factors are ordered by their variance from largest to smallest, and that betas are maximally differentiated in terms of their driving characteristics (achieved by imposing that $\Gamma_\beta'\Gamma_\beta$ equals the identity matrix).

Given this normalization, Figure 2 shows that the first factor is predominantly a spread factor. It has an annualized volatility of 12.7% and an in-sample Sharpe ratio of 1.6.[26] The second factor is dominated by duration. It has an impressive Sharpe ratio of 2.5 and volatility of 9.3%. The third factor is driven largely by bond volatility. The fourth and fifth factors see more characteristics shifting their exposure, adding equity momentum and spread-to-D2D to the aforementioned characteristics.

E. An Observable Factor Model to Approximate IPCA

Our conclusion thus far is that the IPCA model outperforms existing observable factor models by a large margin. It provides a comparatively accurate description of bond market risk (in the form of a high total R^2) and of the compensation earned for exposure to this risk (in terms of both small pricing errors and a high tangency portfolio Sharpe ratio). In this section, we propose a new observable factor model motivated by the IPCA characteristic results above. It delivers an approximation to the empirical performance of IPCA and outperforms previously studied observable factor models.

For observable factors, we use five characteristic-managed portfolios corresponding to the spread, duration, bond volatility, and spread-to-D2D characteristics as well an equal-weighted bond factor (corresponding to the constant characteristic).[27] The first column of Table X reports the out-of-sample performance of this observable factor model configuration using an implementation identical to that for BBW and FF in Table V (in particular, using 36-month rolling betas). It achieves positive out-of-sample total, time-series, and cross-section R^2 (even for individual bonds), easily dominating BBW and FF. The model achieves a relative pricing error of 28% for managed portfolios, which also dominates BBW and FF whose pricing errors are 106% and 38%, respectively. The only dimension along which our proposed observable factor model underperforms BBW and FF is relative pricing error of individual bonds.

[25] The time series of each factor is plotted in the Internet Appendix.

[26] Note that the Sharpe ratio of the spread portfolio in Table I is 0.8, so the efficiency of the first factor benefits significantly from its combination with other characteristics like duration and momentum.

[27] Spread, duration, bond volatility, and the constant stand out as the dominant characteristics according to Table IX. Spread-to-D2D, equity momentum, equity market capitalization, and rating comprise the group of characteristics with the next-largest impact. We use spread-to-D2D due to its sizable role in loadings for factors four and five and its interpretation as a value factor. However, the conclusions of our observable factor analysis in Table X are qualitatively unaffected if we use equity momentum, equity market capitalization, or rating in the place of spread-to-D2D.

Table X

Approximating IPCA with Observable Factors

This table presents out-of-sample total, time-series, and cross-section R^2s and relative pricing errors in percentages for individual bonds (Panel A) and characteristic-managed portfolios (Panel B). Panel C reports out-of-sample systematic bond strategy performance. The observable factors are managed portfolios corresponding to the spread, duration, bond volatility, spread-to-D2D, and constant characteristics. The column labeled "No Instruments" estimates bond and portfolio betas using rolling regressions, as done for competing models in Table V. The column labeled "Instruments" estimates instrumented betas as described in equation (15).

	Observable Factors		
	No Instruments	Instruments	IPCA
Panel A: Individual Bonds (r_t)			
Total R^2	18.5	42.4	50.7
Time-Series R^2	11.8	34.7	44.6
Cross-Section R^2	7.2	30.1	34.0
Relative Pricing Error	171.1	62.9	63.4
Panel B: Managed Portfolios (x_t)			
Total R^2	92.8	93.6	98.5
Time-Series R^2	10.1	25.2	79.0
Cross-Section R^2	83.8	88.1	93.6
Relative Pricing Error	28.0	18.1	1.8
Panel C: Systematic Portfolio Sharpe Ratios			
Tangency	1.72	1.72	6.23
Spread	0.57	2.95	3.53

In the second column of Table X, we report the fits based on the same factors as the first column but using instrumented betas. The functional form for betas is identical to that of IPCA, but (thanks to the factors' observability) the estimation of dynamic betas is simple. Letting g_t denote the set of observable factors, the model takes the form

$$r_{i,t+1} = z_{i,t}' \Gamma_\beta g_{t+1} + \varepsilon_{i,t+1} = \mathrm{vec}(\Gamma_\beta)'(z_{i,t} \otimes g_{t+1}) + \varepsilon_{i,t+1}, \tag{15}$$

where the second equation follows from the matrix product vectorization identity. The implication is that instrumented betas on observable factors are conveniently estimated by a panel OLS regression on observable factors interacted with instruments.

The observable factor model with instrumented betas is competitive with the model fit of IPCA. While the out-of-sample R^2 in the second column is uniformly lower than IPCA, it is substantially better than the "static" beta version in the first column. It has nearly the same pricing error as IPCA for individual bonds (62.9% vs. 63.4%) and reduces the managed portfolio pricing error to 18.1% (vs. 1.8% for IPCA). The instrumented observable factor model is also attractive in terms of systematic bond strategy performance, producing a tangency portfolio Sharpe ratio of 1.72 and a spread portfolio Sharpe ratio 2.95.

The conclusion from this analysis is that an observable factor model including spread, duration, bond volatility, spread-to-D2D, and equal-weighted bond market factors offers a reasonable approximation to the IPCA model. This is especially true when bond factor exposures are instrumented by bond characteristics.

IV. A Structural Perspective

As debt and equity are complementary claims on the value of the underlying firm's assets, their theoretical behavior is tightly linked under the assumption of no arbitrage. In this section, we empirically investigate the structural linkages between debt and equity returns from the perspective of factor pricing models.

A. Factor Model Extension of Schaefer and Strebulaev (2008)

As highlighted by Schaefer and Strebulaev (2008) (SS henceforth), no-arbitrage instantaneous debt and equity returns are related according to

$$\frac{\partial D_{i,t}}{D_{i,t}} = h_{i,t} \frac{\partial E_{i,t}}{E_{i,t}}, \tag{16}$$

where $h_{i,t} = (\frac{1}{\Delta_{E,i,t}} - 1)\frac{E_{i,t}}{D_{i,t}}$ is the capital structure "hedge ratio" and E and D are the firm's equity and debt. The symbol $\Delta_{E,i,t}$ denotes the partial derivative of equity value with respect to firm value, the form of which depends on specifics of the debt contract and the underlying asset value process. SS approximate $h_{i,t}$ with a Merton model for debt and then investigate the no-arbitrage integration of (16) by regressing monthly excess bond returns ($r_{i,t+1}$) on hedged excess equity returns ($h_{i,t} r^E_{i,t+1}$).

SS find that the sensitivity of debt returns to equity is close to that predicted by the Merton model, but the R^2 is far from one. This begs the question, what is the nature of the wedge between credit and equity markets? There are many plausible explanations. Perhaps corporate actions that transfer wealth between debtholders and equityholders (e.g., leveraged buyouts) are a culprit (De Franco et al. (2014)). Another possibility is that microstructure differences induce nonsynchronicity in information assimilation across markets (Bessembinder, Spatt, and Venkataraman (2020)). Both of these hypotheses suggest that the integration wedge would manifest most clearly as a breakdown between the *idiosyncratic* return correlation across market. Other hypotheses would suggest that the integration breakdown occurs in the systematic components of returns. For example, a strong form of market segmentation—in which marginal investors in equity and credit markets are materially different—

would predict that even common risk factors and factor premia are disconnected across markets. IPCA, with its power to flexibly decompose returns into their systematic and idiosyncratic components, is well suited to improve our understanding of the integration wedge.

First, we extend the analysis of SS by separately investigating the integration of (i) the common factor components and (ii) the idiosyncratic components of returns in debt and equity markets. We do so using IPCA to perform the systematic risk decomposition for both markets.

As a preliminary step, because we are working with a different data source and time sample, we replicate the main results of SS using our closest overlap to their original sample. We report these results in the Internet Appendix and establish that, despite some differences in our samples, we achieve a close quantitative match to their published results.

Table XI reports our main analysis of the structural linkage between bond and equity returns. We consider three different dependent variables. One is the entire excess bond return, $r_{i,t+1}$, as in SS. In addition, we separately consider the systematic component ($\beta_{i,t} f_{t+1}$) and idiosyncratic component ($\varepsilon_{i,t+1} = r_{i,t+1} - \beta_{i,t} f_{t+1}$) of the excess bond return based on our estimated five-factor bond IPCA model from Table III. We likewise consider three variations of the equity return on the right-hand side of the regression: the entire excess equity return ($r^E_{i,t+1}$) as in SS, as well as its systematic component ($\beta^E_{i,t} f^E_{t+1}$) and idiosyncratic component ($\varepsilon^E_{i,t+1}$). This equity return decomposition is based on updated[28] estimates of the five-factor equity IPCA model from KPS, who show that this model dominates competing factor-pricing models in describing realized return variation, factor risk exposures, and expected returns among U.S. equities. All regressions in Table XI use the Merton model to construct the structural hedge ratio ($h_{i,t}$) that premultiplies the equity return, following SS. All regressions are pooled panel regressions using bonds from all ratings categories, consisting of 396,179 bond-month observations, with regression standard errors clustered by month.[29]

To establish a baseline for our analysis, the first column of Table XI runs the SS regression of $r_{i,t+1}$ on $h_{i,t} r^E_{i,t+1}$ using our SS-matched sample ending in 2003. We see that the slope coefficient does not significantly differ from 1.0, meaning that the Merton model hedge ratio gives a reasonable approximation for the empirical sensitivity of bond returns to equity returns on average across bonds. Furthermore, the intercept (reported as a percentage) is statistically indistinguishable from zero. We further find that Merton-hedged equity returns explain 9.4% of the panel variation in bond returns. This is a mixed success. On the one hand, were markets fully integrated and bond prices well described

[28] Specifically, we update the data from KPS to match the sample period of our bond data set using the characteristic data set of Jensen, Kelly, and Pedersen (2023). Their data are available through January 2020. We include all of the characteristics from KPS with the exception of sudden unexplained volume (which is not available from Jensen, Kelly, and Pedersen (2023)).

[29] In the Internet Appendix, we discuss the differences between our regression specification and SS.

Table XI
Hedge Ratio Regressions

This table presents panel regressions of excess bond returns ($r_{i,t+1}$) and their systematic ($\beta_{i,t} f_{t+1}$) and idiosyncratic ($\varepsilon_{i,t+1}$) components on hedged equity returns ($r^E_{i,t+1}$) and their systematic ($\beta^E_{i,t} f^E_{t+1}$) and idiosyncratic ($\varepsilon^E_{i,t+1}$) components. The SS matched sample is 1997 to 2003 and main sample is 1999 to 2020. Standard errors are clustered by month and t-statistics are reported in parentheses. Constants are reported in percentages. The number of observations in each regression is 396,179.

	SS Sample	Main Sample											
	$r_{i,t+1}$	$r_{i,t+1}$				$\beta_{i,t} f_{t+1}$				$\varepsilon_{i,t+1}$			
Ind. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$h_{i,t} r^E_{i,t+1}$	1.03	1.47				0.87				0.60			
	(3.58)	(10.82)				(7.26)				(8.40)			
$h_{i,t} \beta^E_{i,t} f^E_{t+1}$			2.29		2.32		2.28		2.29		0.01		0.03
			(8.08)		(8.40)		(8.55)		(8.60)		(0.11)		(0.67)
$h_{i,t} \varepsilon^E_{i,t+1}$				1.02	1.05			0.13	0.16			0.89	0.89
				(8.33)	(8.21)			(2.98)	(3.67)			(9.44)	(9.44)
constant	0.05	0.12	0.09	0.16	0.10	0.11	0.07	0.13	0.07	0.01	0.02	0.02	0.02
	(0.43)	(1.72)	(1.36)	(2.03)	(1.41)	(1.55)	(1.07)	(1.71)	(1.07)	(0.78)	(3.53)	(3.75)	(3.62)
R^2 (%)	9.4	10.1	8.4	3.3	11.9	7.6	18.1	0.1	18.4	3.0	0.0	4.3	4.3

by the Merton model, this R^2 should be closer to one. On the other hand, it is no small feat for a model with a single regressor to capture so much variation in a panel as volatile and heterogeneous as bond returns.

In column (2), we repeat this analysis for our main sample up to 2020. The association between bonds and stocks is moderately stable over time, with a nearly identical proportion of variation explained in the 1999 to 2020 sample as in the sample ending in 2003, although the coefficient does rise significantly above one.

Next, we analyze the relative integration of systematic versus idiosyncratic returns in the two markets. Columns (3), (4), and (5) show that the full bond return ($r_{i,t+1}$) is significantly more sensitive to systematic equity returns ($h_{i,t}\beta^E_{i,t}f^E_{t+1}$) than to idiosyncratic equity returns ($h_{i,t}\varepsilon^E_{i,t+1}$). The univariate R^2s in columns (3) and (four)4) indicate that the systematic equity return is the dominant explanatory variable for bond returns. Column (5) reports the bivariate regression, where we find that the sensitivity of bonds to systematic equity is 2.32, more than double the 1.05 sensitivity to idiosyncratic equity (both are significantly different from zero).

In the next set of regressions, the systematic bond return is the dependent variable. We see that 18.1% of the systematic bond return is explained by systematic equity returns alone (column (7)). In the bivariate regression of column (9), the systematic equity return coefficient is 2.29 and the sensitivity to the idiosyncratic component falls to 0.16. And while the idiosyncratic component is significant, it contributes only 0.1% to the R^2. In other words, the systematic components of bond and equity returns are roughly twice as integrated as their total returns.

In the last set of regressions, idiosyncratic bond returns are the dependent variable. The regressions show that idiosyncratic bond returns are sensitive *only* to idiosyncratic equity returns. The coefficient on systematic equity returns is almost identically zero. Furthermore, the R^2 of 4.3% in the last column shows that idiosyncratic bond and stock returns are substantially less integrated than their systematic counterparts (and less integrated than returns as a whole).

B. Do Bonds and Stocks Share Factors and Factor Premia?

We expand on our analysis of factor model integration across markets by asking whether factors from the equity market price bonds. This question builds on the analysis of Choi and Kim (2018), who emphasize that full market integration implies that markets share the same factors and factor premia.

This hypothesis is particularly well suited for investigation via the instrumented beta framework of IPCA.[30] We begin with the five IPCA equity fac-

[30] A potential limitation of the analysis in Choi and Kim (2018) is their reliance on prespecified factors that KPS argue are insufficient in pricing the cross section of equity returns and are dominated by their IPCA factors. Using a more flexible (and demonstrably more powerful) factor pricing model reduces the likelihood of falsely rejecting the integrated markets hypothesis due to model

Table XII

Equity and Bond Factors

This table presents out-of-sample total R^2s and relative pricing errors in percentages for individual bonds (Panel A) and characteristic-managed portfolios (Panel B). The KPS, FF, and BBW models use the instrumented beta specification for observable factors described in equation (5). Panel C reports out-of-sample performance for model-based systematic bond portfolios.

	Equity Factors		Bond Factors	
	KPS	FF	IPCA	BBW
Panel A: Individual Bonds (r_t)				
Total R^2	10.6	9.6	45.2	−5.6
Relative Pricing Error	44.7	52.8	46.3	92.4
Panel B: Managed Portfolios (x_t)				
Total R^2	32.4	32.0	97.7	−11.7
Relative Pricing Error	18.9	29.2	2.9	43.5
Panel C: Systematic Portfolio Sharpe Ratios				
Tangency	1.90	0.66	6.58	0.44
Spread	2.90	1.54	4.71	0.97

tors (f^E_{t+1}) from our updated estimates of KPS. We embed these in an instrumented beta model for bond returns following the observable factor formulation of equation (15). In this specification, the instruments for bond betas include the same $z_{i,t}$ vector used throughout *plus* the Merton hedge ratios used for Table XI. In this setting, the betas of bonds on equity factors take the interpretation of empirical (rather than structural) hedge ratios. This loosens the restrictive Merton assumptions. In doing so, the "IPCA hedge ratios" can better detect integration between stock and bond markets to the extent it exists in the data.

Table XII reports fits from the estimated equity factor model (column labeled "KPS"). Equity factors are substantially weaker in explaining *realized* bond returns compared to the IPCA bond factor model (column labeled "IPCA"). The equity factor model produces total R^2 values of 10.6% and 32.4% for individual stock and managed portfolios, respectively (compared to 45.2% and 97.7%, respectively, for the IPCA bond factors).[31]

Equity factors, however, fare much better in explaining *expected* bond returns than realized bond returns (note that this is the main dimension along which Choi and Kim (2018) assess the integration of bond and equity markets).

misspecification. See KPS for a discussion of the benefits of latent factor models for confronting the Fama (1970) joint hypothesis problem.

[31] Note that the bond IPCA statistics differ slightly from earlier tables because we lose a small number of observations when we link to the equity sample.

At the individual stock level, KPS equity factors produce relative pricing errors of 44.7%, which are smaller than the 46.3% pricing errors from bond factors. At the managed portfolio level, pricing errors are 18.9% based on equity factors versus 2.9% for IPCA bond factors. As a separate evaluation of bond factor premia, we find that a long-short spread portfolio based on expected bond return estimates from the equity factor model earns a 2.9 annualized out-of-sample Sharpe ratio (the comparable Sharpe ratio from the IPCA bond factor model is 4.7). This again indicates that bond risk premia estimated with the equity factor model align well with the data.

KPS equity factors provide a more favorable view on market integration than implied by equity factors (column labeled "FF"). The KPS versus FF achieve comparable total R^2 for both individual bonds and managed portfolios. Notably, KPS factors achieve lower pricing errors than FF for both individual bonds (44.7% vs. 52.8%) and managed portfolios (18.9% vs. 29.2%). And KPS factors translate into an 88% increase in spread portfolio Sharpe ratio relative to FF. Likewise, it is worth noting that the bond market performance of equity-based factor models exceeds that of previously proposed bond factors in the literature (column labeled "BBW").

As another direct investigation of the similarity between stock and bond factors, we calculate correlations between the factors estimated from the five-factor IPCA specification in each of the markets. Because the factors are not rotationally identified, the appropriate way to assess similarity between factors is to regress each bond factor on *all* equity factors. The multiple correlations ($\sqrt{R^2}$) of each of the five bond factors on all equity factors are 66.4%, 29.8%, 47.3%, 22.2%, and 24.8%, respectively. Like the findings of Table XII, these correlations tell us that while equity factors capture a nontrivial amount of the common variation in realized bond returns, they miss more than they capture.

Finally, we directly compare out-of-sample model-implied risk premia between the equity-based factor model and the bond-based factor model. Focusing on fits at the managed portfolio level, Figure 3 provides a scatterplot of conditional expected bond returns, $\beta_{i,t}\lambda$, based on the bond-based IPCA model on the x-axis versus expected bond returns from the equity-based KPS model on the y-axis. Model-implied bond premia from the two models line up remarkably closely. The correlation is 83.1% between the two models pooling all firm-months. The slope coefficient for the scatterplot's best-fit line is 0.6, indicating that the bond-based factor model produces more dispersion in bond risk premia than the equity-based model.

We find similarly close alignment among different bond risk premia estimates when we use the FF five equity factors rather than the KPS equity factors (see the Internet Appendix). The bond risk premia from our main IPCA model have a 72% correlation with bond premia estimated based on the FF factors (with instrumented betas), and the scatterplot slope coefficient is 0.26 (highly statistically significant). Thus, while IPCA estimates isolate the integration of bond and equity markets with more precision, one reaches the same qualitative conclusion with prespecified equity factors.

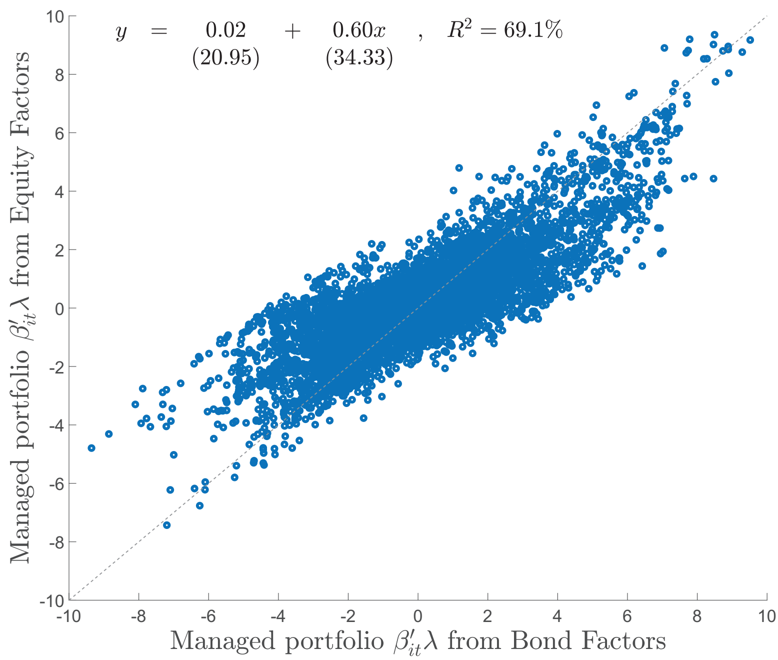

Figure 3. Bond risk premium comparison. The figure shows out-of-sample estimates for conditional expected bond returns, $\beta_{i,t}\lambda$, based on the bond-based IPCA model on the x-axis and the equity-based KPS model on the y-axis. We also report the estimated regression equation for the best-fit line. (Color figure can be viewed at wileyonlinelibrary.com)

To summarize, by honing in on the systematic variation in bond returns and the joint factor structure among equity and debt, we find stronger evidence of integration between stock and bond markets than previously reported in the literature. Systematic bond returns are nearly twice as sensitive to their systematic equity counterparts as one would estimate by looking at the total return. This finding helps differentiate among theories on the determinants of imperfect integration between stock and bond markets. In particular, the very low integration of idiosyncratic returns suggests that limits to arbitrage plays a first-order role in integration breakdown, while the high degree of sensitivity between systematic returns of equity and debt indicates that market segmentation is a comparatively smaller impediment to integration.

We also find that while equity-based factors have notably less ability than bond-based factors to describe realized variation in bond returns, equity-based factors deliver a remarkably close quantitative match (a correlation in excess of 80%) to the bond risk premia recovered from the bond-based factor model. Choi and Kim (2018) conclude from their analysis that "Overall, we find it difficult to reconcile the magnitudes of bond return premia with those of equity return premia." Our structural analysis, through the lens of the IPCA factor modeling framework, reaches a more positive view regarding market integration. The clearest economic conclusion from our analysis is that debt and equity markets are more integrated than previous estimates suggest, and that these markets are substantially more integrated in terms of their systematic risks than their idiosyncratic risks.

V. Conclusion

We propose a conditional model of corporate bonds returns based on IPCA. The core idea is that bond and firm characteristics provide valuable conditioning information for accurately estimating bonds' exposures to aggregate risk factors. The model embeds the economic restriction that characteristics useful for forecasting conditional expected bond returns do so because they also help predict factor betas for bonds.

We show that our IPCA bond model surpasses leading factor models for corporate bond returns in prior literature. In particular, it explains more variation in realized bond returns, yields better predictions of future bond returns, and results in smaller pricing errors (both in-sample and out-of-sample). Optimal trading strategies derived from the estimated model are remarkably profitable, even net of trading costs. By comparing equity and debt returns, our results identify stronger market integration than documented in previous literature, and demonstrate that this integration is particularly strong among the systematic components of debt and equity returns.

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Appendix A: Characteristics Description

The following describes characteristics outlined in Table AI. Bond age is measured in years. Coupon, face value, and are attributes of the bond issue. Spread is the option-adjusted spread of the bond. Rating is a number from 1 to 22, where 1 is S&P AAA and 22 is already in default. Book-to-price is the sum of shareholders' equity and preferred stock divided by equity market capitalization for the issuing firm. Debt-to-EBITDA uses total debt. Duration is the derivative of the bond value to the credit spread divided by the bond value and is calculated by the data vendor's proprietary pricing model. Mom. 6m equity is 6-2 momentum of the firm's stock returns; mom. 6m is 6-2 momentum of bond returns; mom. 6m industry is industry-adjusted 6-2 momentum of bond returns; mom. 6m $\times$ ratings is bond return momentum times the numerical rating; mom. 6m log(Spread) is the log of the spread six months earlier minus current log spread. Book leverage shareholder's equity and long-/short-term debt and minority interest minus cash and inventories, divided by shareholder's equity minus preferred stock. Market leverage is market cap and long-/short-term debt and minority interest and preferred stock

Table AI

Characteristics

This table presents the set of characteristics that we consider, with references to previous literature. The characteristics are described in detail in the Appendix text.

1.	Bond age—Israel, Palhares, and Richardson (2018)
2.	Coupon—Chung, Wang, and Wu (2019)
3.	Face value—Israel, Palhares, and Richardson (2018)
4.	Book-to-price—Bartram, Grinblatt, and Nozawa (2020)
5.	Debt-to-EBITDA
6.	Duration—Israel, Palhares, and Richardson (2018)
7.	Mom. 6m equity—Gebhardt, Hvidkjaer, and Swaminathan (2005b)
8.	Earnings-to-price—Correia, Richardson, and Tuna (2012)
9.	Equity market cap.—Choi and Kim (2018)
10.	Equity volatility—Campbell and Taksler (2003)
11.	Firm total debt
12.	Mom. 6m—Gebhardt, Hvidkjaer, and Swaminathan (2005b)
13.	Mom. 6m industry—Jorion and Zhang (2009)
14.	Mom. 6m $\times$ ratings—Avramov et al. (2007)
15.	Book leverage—Asness, Frazzini, and Pedersen (2019)
16.	Market leverage—Asness, Frazzini, and Pedersen (2019)
17.	Turnover volatility—Correia, Kang, and Richardson (2018)
18.	Spread—Israel, Palhares, and Richardson (2018)
19.	Operating leverage—Gamba and Saretto (2019)
20.	Profitability—Choi and Kim (2018)
21.	Profitability change—Asness, Frazzini, and Pedersen (2019)
22.	Rating
23.	Distance-to-default—Israel, Palhares, and Richardson (2018)
24.	Bond skewness—Bai, Bali, and Wen (2019)
25.	Mom. 6m log(Spread)—Israel, Palhares, and Richardson (2018)
26.	Spread-to-D2D—Correia, Richardson, and Tuna (2012)
27.	Bond volatility—Bai, Bali, and Wen (2019)
28.	Value-at-risk—Bai, Bali, and Wen (2019)
29.	VIX beta—Chung, Wang, and Wu (2019)

minus cash and inventories, divided by market cap. Turnover volatility is the quarterly standard deviation of sales divided by assets. Operating leverage is sales minus EBITDA, divided by EBITDA. Profitability is sales minus cost-of-goods-sold, divided by assets, for nonfinancials; it is sales minus total expenses plus depreciation, divided by shareholder's equity minus preferred stock, for financials. Profitability change is the five-year change in profitability. Distance-to-default is defined by Shumway (2001). Bond skewness is bond return skewness over the past 60 months. Spread-to-D2D is the option-adjusted spread, divided by one minus the cumulative distribution function of the Shumway distance-to-default. Bond volatility is bond return volatility over the past 24 months. Value-at-risk is the second lowest credit excess return over the past 36 months, with a minimum of 24 months. VIX beta is the sum of coefficients on current and lagged VIX in a regression of bond returns on Mkt-RF, HML, SMB, DEF, TERM, VIX, and lagged VIX, run over the past 60 months.

Table BI
IPCA Asset Pricing Test

This table presents bootstrapped p-values in percentages for a test of the null hypothesis $\Gamma_\alpha = 0$ in equation (B1). We use a wild-bootstrap following KPS using a t-distribution with seven degrees of freedom and 1,000 simulations.

	K				
	1	2	3	4	5
p-Value for H_0: $\Gamma_\alpha = 0$	0.0	0.0	0.0	0.0	2.6

Appendix B: Constrained Alpha Specification

In this section, we discuss a constrained alpha specification of the instrumented principal components analysis (IPCA) model as originally proposed by Kelly, Pruitt, and Su (2019) (2021). It takes the form

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1}, \tag{B1}$$

$$\alpha_{i,t} = z'_{i,t}\Gamma_\alpha, \quad \beta_{i,t} = z'_{i,t}\Gamma_\beta.$$

One of our null hypotheses throughout the paper is that bonds are priced by a conditional factor model with no alpha. This corresponds to restricting conditional intercepts $\alpha_{i,t}$ to zero for all bonds at all points in time. We also consider a constrained alternative hypothesis that allows for nonzero Γ_α which represents the possibility that conditional expected bond returns are predictable by characteristics but *not* through betas. Under the alternative hypothesis, IPCA estimates $\alpha_{i,t}$ by finding the linear combination of characteristics that best describes conditional expected returns while controlling for the role of characteristics in factor risk exposure. If characteristics align with average bond returns *differently* than they align with risk factor loadings, then IPCA will estimate a nonzero Γ_α vector, thus identifying compensation for holding bonds that does not align with their systematic risk exposure.

To estimate this form, we find the values of $(\{f_{t+1}\}, \Gamma_\beta, \Gamma_\alpha)$ that minimize the sum of squared model errors. We then conduct the bootstrap test of the null hypothesis H_0: $\Gamma_\alpha = 0$ by comparing the null model with estimates of the unrestricted ($\Gamma_\alpha \neq 0$) specification, as described by KPS. The results are shown in Table BI.

Appendix C: Return Scaling

Our main analysis studies returns divided by Duration times Spread (DtS). This produces returns that are on homogeneous volatility footing. In Table CI, we analyze the robustness of our results to using either unscaled returns (Panel A) or returns scaled by historical volatility (Panel B).[32] The table reports

[32] Like the DtS adjustment, we winsorize the lower tail of volatility before scaling returns: $r_{i,t+1} = \frac{\tilde{r}_{i,t+1}}{\max(Vol_{i,t}, \underline{Vol})}$ where $\underline{Vol}$ equals 1%, which is roughly the 20th percentile of volatility in our

Table CI

IPCA Out-of-Sample Performance with Alternative Return Scaling

This table repeats the analysis of Table IV but instead uses either unscaled returns (Panel A) or volatility-scaled returns (Panel B).

	K				
	1	2	3	4	5
Panel A: Unscaled Returns					
Individual Bonds (r_t)					
Total R^2	38.5	42.1	44.1	45.3	45.9
Time-Series R^2	16.8	16.6	19.7	18.6	20.0
Cross-Section R^2	25.2	26.8	28.9	29.9	30.5
Relative Pricing Error	45.1	41.1	45.5	46.8	45.4
Managed Portfolios (x_t)					
Total R^2	87.6	92.6	95.1	96.3	96.7
Time-Series R^2	41.6	63.1	73.4	79.1	81.2
Cross-Section R^2	74.9	79.7	85.6	88.2	89.7
Relative Pricing Error	14.8	12.7	13.5	5.4	2.7
Panel B: Volatility-Scaled Returns					
Individual Bonds (r_t)					
Total R^2	43.9	48.8	50.0	53.1	54.4
Time-Series R^2	36.9	39.7	40.6	44.5	46.4
Cross-Section R^2	26.2	28.7	30.5	32.0	34.2
Relative Pricing Error	52.3	54.0	49.6	52.3	51.8
Managed Portfolios (x_t)					
Total R^2	88.6	92.9	93.9	96.9	97.8
Time-Series R^2	10.4	42.0	52.1	72.5	78.5
Cross-Section R^2	75.9	81.2	85.3	88.9	92.1
Relative Pricing Error	55.2	43.0	45.4	19.9	2.7

the same out-of-sample fit metrics as in Table IV, and shows that the choice of return scaling has little bearing on model fit. For unscaled and volatility-scaled returns, the $K = 5$ R^2 statistics and relative pricing errors are roughly the same magnitude as we find for DtS-scaled returns.

In Table CII, we report the out-of-sample factor tangency portfolio Sharpe ratios for samples of unscaled and volatility-scaled returns. IPCA factors remain highly efficient in terms of their risk-return trade-off. This is true after accounting for trading costs and when smoothing tangency portfolio weights. The lower Sharpe ratios for unscaled returns reflect the fact that DtS-scaling and rolling-volatility-scaling allow the model to better hone in on the conditionally-efficient factor model. Nonetheless, even the model of unscaled returns substantially outperforms the factor tangency portfolios from Bai, Bali, and Wen

sample. Like DtS-scaling, the role of volatility scaling is to downweight high volatility bonds to robustify the behavior of least squares estimates.

Table CII

IPCA Tangency Portfolio with Alternative Return Scaling

This table repeats the analysis of Table VIII for the tangency portfolio, but is instead based on the $K = 5$ IPCA model with either unscaled returns or volatility-scaled returns.

	Turnover		Gross Sharpe Ratio		Net Sharpe Ratio	
γ	Unscaled	Vol-Scaled	Unscaled	Vol-Scaled	Unscaled	Vol-Scaled
0.0	0.60	0.68	2.67	4.94	1.35	2.11
0.1	0.55	0.63	2.62	4.90	1.40	2.26
0.2	0.50	0.57	2.55	4.81	1.41	2.36
0.3	0.46	0.53	2.44	4.67	1.40	2.42
0.4	0.42	0.48	2.29	4.46	1.34	2.42
0.5	0.38	0.43	2.08	4.16	1.25	2.35
0.6	0.33	0.39	1.83	3.72	1.12	2.19
0.7	0.29	0.33	1.53	3.16	0.96	1.94
0.8	0.23	0.28	1.20	2.47	0.78	1.58
0.9	0.17	0.20	0.84	1.63	0.57	1.09

(2019) (BBW) and Fama and French (2015) (FF) reported earlier. In the Internet Appendix, we report model fits of IPCA versus BBW and FF for the unscaled return sample. The results demonstrate that our conclusions regarding model comparisons are also robust to alternative scaling choices.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.