Internet Appendix for

Forecasting Corporate Bond Returns with a Large Set of Predictors: An Iterated Combination Approach

In this separate Internet Appendix, we describe details of the data used in the paper and report additional empirical results that supplement our findings. In Section A, we explain how we construct 27 predictors and corporate bond portfolios used in the paper. In Section B, we report the results of additional empirical tests.

A Data

A.1 Predictors

From the literature of equity return forecasts (Welch and Goyal, 2008), we consider the following 14 variables as predictors.

1. Dividend-price ratio (log), D/P: Difference between the log of dividends paid on the S&P 500 index and the log of stock prices (S&P 500 index), where dividends are measured using a one-year moving sum.

2. Dividend yield (log), D/Y: Difference between the log of dividends and the log of lagged stock prices.

3. Earnings–price ratio (log), E/P: Difference between the log of earnings on the S&P 500 index and the log of stock prices, where earnings are measured using a one-year moving sum.

4. Dividend–payout ratio (log), D/E: Difference between the log of dividends and the log of earnings.

5. Stock return variance, SVAR: Sum of squared daily returns on the S&P 500 index in a month.

6. Book-to-market ratio, B/M: Ratio of book value to market value for firms included in the Dow Jones Industrial Average.

7. Net equity expansion, NTIS: Ratio of the twelve-month moving sum of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.

8. Treasury bill rate, TBL: Interest rate on a three-month Treasury bill (secondary market).

9. Long-term yield, LTY: Long-term government bond yield.

10. Long-term return, LTR: Return on long-term government bonds.

11. Term spread, TMS: Difference between the long-term yield and the Treasury bill rate.

12. Default yield spread, DFY: Difference between BAA- and AAA-rated corporate bond yields.

13. Default return spread, DFR: Difference between long-term corporate bond and long-term government bond returns.

14. Inflation, INFL: Calculated from the CPI (all urban consumers).[1]

In addition, we use a number of variables considered to be important for predicting bond returns from the literature (see Collin-Dufresne, Goldstein and Martin, 2001; Baker, Greenwood and Wurgler, 2003; Cochrane and Piazzesi, 2005; Næs, Skjeltorp, and Ødegaard, 2011; Greenwood and Hanson, 2013). We discuss each of these variables below.

Stock market returns and the aggregate leverage ratio

Collin-Dufresne, Goldstein and Martin (2001) show that stock returns and leverage are important structural variables explaining yield spread changes. We use the monthly S&P 500 index returns as a measure of the equity market return. For leverage, we use two aggregate leverage measures. First, we average the leverage ratios of individual stocks listed in NYSE to give a measure of market aggregate leverage ratio (LEV1). The leverage ratio of an individual stock is measured by the book value of debt divided by the sum of the book value of debt and market value of equity, where the book value of debts is the sum of long-term debts and current liabilities obtained from COMPUSTAT. Second, we use the ratio of the aggregate book value of debt to the sum of aggregate book value of debt and market value of stocks listed in NYSE as another leverage measure (LEV2). The aggregate book value of debt and the aggregate market value of equity are the sum of book value of debt and the sum of equity value for all stocks listed in NYSE.[2] As the COMPUSTAT data used are quarterly, a linear interpolation is used to obtain monthly estimates (see also Collin-Dufresne, Goldstein and Martin, 2001). The market value of equity is the product of share price and the outstanding number of shares from the CRSP.

The Cochrane-Piazzesi term structure factor

Cochrane and Piazzesi (2005, hereafter CP) find that a single factor constructed from the full term structure of forward rates has high predictive power on excess returns of Treasury bonds. Lin, Wang and Wu (2014) find that the CP factor has predictive power for corporate bond returns.

[1] Data were downloaded from Amit Goyal's website. These variables are used in Welch and Goyal (2008) and Rapach, Strauss and Zhou (2010). Also, since inflation rate data are released in the following month, following Welch and Goyal (2008), we use the one-month lag inflation data.

[2] When calculating the aggregate leverage ratio, we only use the stocks in NYSE that have financial statement data in COMPUSTAT.

Following CP (2005), we use the Fama-Bliss data of one- through five-year zero-coupon bond prices (available from CRSP) from 1973 to 2012 to estimate forward rates and their regression coefficients in the CP model, and construct the CP 5-year forward rate factor. Besides the CP 5-year factor, we construct a CP 10-year factor using the forward rates up to 10th year similar to Lin, Wang and Wu (2014) to capture the information in distant forward rates. Note that the 5- and 10-year CP forward factors are computed in real time, not based on the full sample. We only use the available data up to the time of forecast to estimate the CP factors and to forecast future returns and so there is no look-ahead bias.

The issuer quality factor

Greenwood and Hanson (2013) find that time-series variations in the average quality of debt issuers are useful for forecasting excess corporate bond returns. We include this variable as a predictor for bond returns. Similar to their study, we use the fraction of non-financial corporate bond issuances in the last 12 months with a junk rating as the issuer quality factor,

$$IQ_t = \frac{\sum_{j=0}^{j=11} Junk_{t-j}}{\sum_{j=0}^{j=11} Invest_{t-j} + \sum_{j=0}^{j=11} Junk_{t-j}}, \tag{1}$$

where $Junk_t$ is the par value of issuance with a speculative grade, and $Invest_t$ is the par value of issuance with an investment grade in month t. The monthly investment/junk bond issues for the period 1973–1993 are obtained from the Warga tape, and the monthly investment/junk bond issues for the period beginning from 1994 are obtained from FISD. High IQ_t tends to be followed by low corporate bond returns. For ease of interpretation, we add a negative sign to IQ_t to convert it into a bond quality measure, a higher value of which indicates better quality. This transformation makes the predictive relationship positive between quality of issuers and bond returns.

The debt maturity factor

Baker, Greenwood and Wurgler (2003) find that the share of long-term debt issues in total debt issues can predict government bond returns. It is possible that this predictor may also forecast corporate bond returns. We obtain the outstanding amounts of annual long- and short-term debts from the Federal Reserve Bank database and construct the monthly series of long- to short-term debt ratios using a linear interpolation. Baker, Greenwood and Wurgler (2003) find that when the share of long-term issues in the total debt issues is high, future bond returns are low.

The liquidity factor

The literature has documented a strong predictive relation between stock market liquidity and business cycle (see, for example, Næs, Skjeltorp, and Ødegaard (2011)). Since asset risk premia are related to business conditions, this finding implies that aggregate liquidity may predict corporate bond returns. We consider different liquidity measures including monthly changes in total money market mutual fund assets (ΔMMMF), on-/off-the-run spreads (Onoff), and the effective cost (EC) index of Hasbrouck (2009) for the stock market as predictors. Data for money market mutual fund assets are obtained from the Federal Reserve Bank. The on-/off-the-run spread is taken from the difference between the five-year constant-maturity Treasury rate from the Federal Reserve Bank and the five-year generic Treasury rate reported by Bloomberg system (see Pflueger and Viceira, 2011). The spread between on- and off-the-run bond yields captures the liquidity of the Treasury bond market (Duffie, 1996; Longstaff, Mithal and Neis, 2005). The spread may also reflect the financing advantage of on-the-run Treasury securities in the special repo market (Jordan and Jordan, 1997; Buraschi and Menini, 2002; Krishnamurthy, 2002).

As liquidity has many dimensions, we use additional liquidity indices to capture more information. Two widely used marketwide liquidity indices in the literature are Pastor-Stambaugh (2003, PS) and Amihud (2002, Am) stock liquidity measures. The PS stock liquidity measure (PSS) is available from WRDS. We construct the Amihud stock (AmS) measures using the methods suggested by Acharya and Pedersen (2005). For ease of comparison with other illiquidity measures, we add a negative sign to the PS liquidity measure to make it consistent with the on-/off-the-run spread and Amihud measures, both are proxies for illiquidity. The converted PS index becomes a measure of market illiquidity.

Portfolios' yield spreads

Previous studies have found the bond yield contains important information for future bond returns (see, for example, Keim and Stambaugh, 1986; Greenwood and Hanson, 2013). However, the major information content of bond yields for expected corporate bond returns (or risk premium) should be associated with yield spreads. To see why this is the case, consider the pricing formula of a corporate bond at time t:

$$P(y_t,t) = \sum_{i=1}^{i=n} Ce^{-y_t(T_i-t)} + FVe^{-y_t(T_n-t)}, \tag{2}$$

where C is the periodic coupon payment, y_t is the yield to maturity at time t, FV is the face value, and $T_i, i = 1,...,n$ is the time of the ith payment. Using the Taylor expansion, we can approximate the bond's excess return by

$$r_{t+1} = -D_t\Delta y_t + y_t - r_f^t, \tag{3}$$

where D_t is the duration of corporate bond at time t. Results show that the portfolio's yield spread (PYS), $y_t - r_f^t$, is a predictor for corporate bond excess returns.[3] Therefore, we include the yield spread as the predictor for bond returns. It is important to note that this predictor is distinguished

[3]Lin, Wang and Wu (2014) also find that the duration-adjusted portfolio yield spread is useful for the prediction of corporate bond returns but they did not provide a rationale why yield spreads have information for expected bond returns.

from the default yield spread (DFY) of Fama and French (1989). The yield spread variable considered here is bond-specific. In empirical investigation, we test the predictability of bond portfolio returns. We hence calculate the yield spread for each rating and maturity portfolio for the predictive regression but this spread variable is still portfolio-specific.

Table IA1 provides summary statistics for each predictive variable.

[Insert Table IA1 about here]

A.2 Bond data

Table IA2 summarizes the distribution of corporate bond data. Panel A shows that the data sample is well balanced across maturities and ratings. A-rated bonds assume the largest proportion, which have 302,794 observations and account for 40% of the sample. The speculative-grade bonds account for more than 10% of the sample, with 86,441 bond-month observations. Across maturities, long-term bonds (with maturity greater than 10 and less than 30 years) have the largest proportion. Among the data sources, LBFI contributes the most to the data sample (261,821 observations), followed by TRACE (261,063 observations), Datastream (147,486 observations) and NAIC (110,615 observations).

[Insert Table IA2 about here]

Panel B of Table IA2 reports summary statistics for rating and maturity portfolios. The left panel reports the results of equal-weighted portfolios, while the right panel reports the results of value-weighted portfolios. Both mean and standard deviation of excess returns increase as the rating decreases. Long-maturity portfolios have higher mean returns and standard deviation.

To bring out the dynamics of bond returns, we transform the excess return series into the index (cumulative excess return) series by

$$I_t = I_{t-1}(1 + r_t),$$

where r_t is the excess return of a corporate bond portfolio in month t. The initial value at time 1, which is January 1973 in our paper, is set to be 100. Thus, when there is a decrease in the index in month t, it means that the return of the portfolio is negative for that month.

Figure IA1 plots the time series of the indices for all rating portfolios. The upper panel plots the indices of equal-weighted portfolios, while the middle panel plots the indices of value-weighted portfolios. There is an uptrend in these indices, suggesting that the investment in the corporate bond markets provides positive excess returns. However, in times of stress (such as the internet bubble in 2000, and the recent financial crisis in 2008–2009), the return drops substantially for junk bonds but remains quite smooth for AAA bonds. This pattern is attributable to flight-to-quality during the crisis period. In empirical tests, for brevity we only report results of value-weighted portfolios.

Our empirical tests are primarily based on the time series of corporate bond portfolio returns. Using the returns of portfolios constructed from the database of individual bonds allows us to control for the effects of bond provisions. We construct the portfolio return series by excluding bonds with embedded options (e.g., callable, putable and sinkable) to avoid the confounding effects associated with these options. Another advantage of using the return series constructed from the database of individual bonds is that we are able to obtain a longer time span for the return series. By contrast, existing indices of corporate bond returns do not have a unbroken long-span time series. Older corporate bond indices such as Salomon Brothers indices were suspended in 2001 while newer indices such as Barclays corporate bond indices are available only starting in 1987. The shorter time span of these index return series results in lower power in empirical tests. Also, these publicly available indices do not control for the effects of bond provisions and so are subject to the confounding effects of embedded options. Despite these drawbacks, we also report test results based on the Barclays index return series for comparative purposes and robustness check. The bottom panel of Figure IA1 plots the return series of the Barclays indices which are obtained from the Bloomberg System. As shown, our portfolio returns exhibit a similar temporal pattern as Barclays corporate bond index returns.

[Insert Figure IA1 about here]

B Additional empirical tests

B.1 Univariate in-sample predictive regression

The left panel of Table IA3 reports in-sample R^2 values of the predictive regressions for each predictor listed in Table IA1. The left side of the left panel reports results of monthly forecasts, and the right side shows quarterly forecasts. All monthly forecasts are based on monthly non-overlapping bond returns and quarterly forecasts are based on overlapping bond returns where quarterly returns is the sum of current and past two monthly returns throughout this paper. Returns are all based on log returns.

The results indicate that a number of variables associated with the stock and bond markets can predict corporate bond returns in-sample with a high R^2. Besides default spreads (DFY) and portfolios' yield spreads (PYS), variables with predictive power include term spreads (TMS), on-/off-the-run spreads (Onoff), and changes in money market mutual fund flows (ΔMMMF), long-term government bond returns (LTR), inflation rates (INFL), the Cochrane-Piazzesi forward rate factors (CP5 and CP10), leverage ratio (LEV2), earning-price ratio (E/P), dividend-payout ratio (D/E) and stock return variance (SVAR). These variables have R^2s higher than or comparable to that of default spreads.

Consistent with Joslin, Priebsch and Singleton (2014), we find that macroeconomic factors contain important information for expected corporate bond returns. More importantly, predictive variables vary in their ability to track bond returns of different rating classes. For AAA bonds, Treasury market variables such as long-term government bond returns (LTR), term spreads (TMS), Cochrane-Piazzesi forward rate factor (CP10), and on-/off-the-run spreads have good predictive power. In contrast, for speculative-grade bonds, stock market variables like earnings yields (E/P), dividend payout (D/E), and leverage ratio (LEV2), and default yield spreads (DFY) that are closely related to business and credit risks have high predictive power. In addition, on-/off-the-run spreads have high predictive power, which appears to capture market liquidity conditions that affect all bonds. The main message we get from this table is that the best predictors for high-quality bonds are those that forecast the term structure whereas the best predictors for junk bonds are those that forecast credit risk premia.

[Insert Table IA3 about here]

To see the individual relation between bond returns and predictors more closely, we report the covariance of each standardized predictor with bond returns in the right panel of Table IA3. Since each predictor is standardized to have variance equal to one, the covariance is effectively the slope coefficient of the regressor in the univariate regression. Furthermore, the covariance of each predictor with bond returns reflects the weight or loading on each predictor when combining all variables into a single forecaster using either the PLS or our IMC method. As shown in the table, many of the predictive variables are significant (in boldface).

The results show that the traditional predictors, such as term spreads (TMS), default spreads (DFY), and Treasury bill rates (TBL), are indeed closely related to expected bond returns. More importantly, the stock market variables and other bond market variables also have high covariances with bond returns. These include earning yields (E/P), dividend payout (D/E), leverage ratios (LEV1 and LEV2), long-term government bond returns (LTR), inflation rates (INFL), CP factors (CP5 and CP10), percentage changes in the money market mutual fund flows (ΔMMMF) and on-/off-the-run spreads (Onoff). For the monthly horizon, on average the on-/off-the run spread has the largest covariance with returns. For the quarterly horizon, on average the portfolio yield spread PYS has the largest covariance with returns, followed by the CP10 forward rate factor. The fact that these variables are highly correlated with bond returns suggests that it is important to consider other variables than traditional predictors in forecasting corporate bond returns.

A particularly interesting finding that has an important economic implication and interpretation is that returns of low-grade bonds are more closely related with stock market variables. For example, the covariances of returns with earning yields (E/P), dividend payout (D/E), stock return volatility (SVAR), S&P 500 index returns (S&P 500), aggregate leverage ratios (LEV1 and

LEV2), and effective trading cost (EC) are all highest for junk bonds, suggesting that stock market variables better track expected returns of these speculative bonds. This finding strongly supports the traditional view that speculative-grade bonds behave like stocks. Moreover, low-grade bond returns are closely linked to corporate bond market variables that are intimately related to credit risk premia. The covariances (slopes) of returns with default yield spread (DFY), issuance quality index (IQ), debt maturity index (DM) and portfolio yield spreads (PYS) are all highest (in absolute terms) for speculative-grade bonds. These findings provide clear evidence that the expected return of low-grade bonds contains a risk premium that is more strongly related to longer-term business and credit market conditions.

The results in Table IA3 reflect rational pricing in the corporate bond market. The sign of the predictive variables is consistent with the risk premium theory. As shown, the slopes are positive for term spreads, default spreads, and the CP forward rate factor. These variables are well known measures of business cycles. The positive slopes of these variables capture the risk premia in bond returns which increase with business and interest rate risks. In addition, stock market predictive variables such as D/E, stock market volatility (SVAR), and leverage ratios (LEV) have positive slopes and E/P has a negative slope. This pattern is consistent with the rational asset pricing theory that when business-conditions risk is high or earnings are low, risk premia are high. Similarly, the slopes of credit risk variables such as DFY, IQ, PYS are positive while that of DM is negative. Consistent with the risk premium theory, the slope coefficients of all of these variables increase (in absolute terms) from high-grade to low-grade bonds. This trend is in line with the intuition about the credit risk of bonds, which is highly correlated with the business condition. Results show that the sensitivity of bond returns to unexpected changes in business and credit risks increases as the bond rating decreases. The slopes suggest that these predictive variables track components of expected corporate bond returns that vary with business and credit risk conditions.

B.2 Encompassing test results

To further evaluate the performance of different models, we conduct forecast encompassing tests. If the IWC forecaster has successfully extracted all relevant information in individual predictors, then adding the variables in the Fama-French and Greenwood-Hanson models should not improve the forecasting power of the IWC model. The encompassing test discriminates the performance of competing models based on this criterion.

We calculate the HLN statistics of Harvey, Leybourne, and Newbold (1998) to test whether the forecast by the IWC model encompasses the forecasts by the FF, GH and PCA models or vice versa. The null hypothesis is that model 1 forecast encompasses model 2 forecast, against the one-sided alternative that the former does not encompass the later. Table IA4 reports the results of encompassing tests based on monthly return forecasts for different ratings and maturities. As shown, the IWC model encompasses the FF, GH, and PCA models, suggesting that the IWC is more efficient than the other three models in utilizing the information of individual predictors. By contrast, the FF, GH and PCA models all fail to encompass the IWC model. Results strongly suggest that the IWC model contains all information in the FF, GH and PCA models. Unreported results show a similar finding at the quarterly forecast horizon. These findings confirm the superiority of the IWC model and suggest that it provides the optimal forecast for corporate bond returns relative to other models.

[Insert Table IA4 about here]

B.3 Alternative models

Following the literature on return predictability, we have employed the linear predictive regression as the baseline model in performing forecasts. In this section, we further explore two alternative predictive nonlinear models for forecasting returns.

Consider first the GARCH (1,1) process

$$r_{t+1} = a_j + b_j z_{jt} + \varepsilon_{t+1,j},$$

where $\varepsilon_{t+1,j} \sim N(0, \sigma^2_{t+1,j})$, and $\sigma^2_{t+1,j} = \gamma_{0,j} + \gamma_{1,j}\sigma^2_{t,j} + \gamma_{2,j}\varepsilon^2_{t,j}$. It is widely known that this GARCH-type model captures time-varying return volatility and it will be interesting to check the robustness of the iterated combination forecasts to this return process. In this model, we estimate the slopes based on the GARCH (1,1) process recursively to obtain the out-of-sample forecasts. In this nonlinear case, both IWC and IMC can be applied to forecast combinations but the PLS cannot. As such, the IMC is differentiated from the PLS, and our iterated combination approach is the only alternative available to further improve the MC or WC forecasts.

Consider next the case with constraints on forecasts. Following Campbell and Thompson (2008) and Pettenuzzo, Timmermann and Valkanov (2014), while still keeping the GARCH (1,1) process above, we can impose the following parametric restrictions

$$0 \leq \hat{r}_{t+1,j} \leq 2\sigma_{t+1,j}/\sqrt{1/T}, j = 1,..,27.$$

These restrictions impose a non-negative risk premium and confine the annualized Sharpe ratio to a range between zero and two.

To demonstrate the flexibility of our iterated combination approach, we employ the above two nonlinear models to perform out-of-sample forecasts. Table IA5 reports the monthly results for the two extended models. For the illustrative purpose, we only report the results for the forecast of junk bond returns for brevity; forecasts of other rating groups show a similar pattern. Compared with the results reported in Tables 2 and 3, these extended models moderately improves the out-of-sample forecast. For example, the overall monthly R^2_{OS} of junk bonds in Table 2 is 11.34% for the IWC. It increases to 11.99%, and 11.70% respectively for nonlinear Models 1 and 2 in Table IA5. The results for economic significance also show a clear improvement for the unrestricted GARCH model and a significant gain by using the IWC. Note that the truncation approach used in Model 2 is different from that of Pettenuzzo, Timmermann and Valkanov (2014). Pettenuzzo, Timmermann and Valkanov (2014) employ the economic constraints to modify the posterior distribution of parameters and to enable the model to learn from the data. Extending the current estimation procedure to accommodate this more sophisticated method should further improve the performance of the IWC model as Pettenuzzo, Timmermann and Valkanov (2014) argue so persuasively. Implementing this computationally extensive procedure is however beyond the current scope of this paper and it can be better dealt with in a separate study.

[Insert Table IA5 here]

B.4 Predictions using Treasury market variables vs. other market variables

An important issue is about the roles of Treasury market variables versus other market variables in predicting corporate bond returns. Safe bonds (e.g., AAA) behave more like government bonds and risky bonds (e.g., junks) behave more like stocks. Intuitively, the former is likely to be affected more by Treasury market variables (e.g., discount rates) and the latter more by the variables of the stock and other markets such as high-yield bonds. In words, Treasury market variables should track the premia for safe bonds more closely, and stock market variables and credit risk variables in the corporate bond market should track the premia for risky bonds better. Table IA3 has provided some evidence for supporting this argument. In this section, we test this hypothesis more formally. We construct the IWC predictor using only Treasury market variables and calculate its out-of-sample R^2 of corporate bond return forecasts. The difference between the out-of-sample R^2 of the IWC predictor extracted from Treasury market variables and that of the IWC predictor based on all variables, including stock, corporate bond and Treasury market variables, measures the contribution of the predictive variables other than Treasury market variables to return forecasts.

We use different criteria to determine whether bonds have the characteristics of government bonds or stocks. Besides the rating, we consider default risk measured by expected default frequency (EDF) estimated from the Merton (1974) model, and stock market return betas. We employ the iterative procedure suggested by Bharath and Shumway (2008) and Gilchrist and Zakrajšek (2012) to estimate the EDF from the Merton model. To estimate market return betas, we run regressions of individual bond excess returns using a two-factor model with the term spread and stock market returns. The term spread factor is measured by the return difference between long-term government bond and one-month Treasury bill rates and the stock market factor is measured by the excess return of S&P 500 index. The term spread captures the effect of interest rates whereas the S&P 500 index return captures the effect of the market factor. We use the beta of stock market returns to sort the bonds into quintile portfolios. The portfolio return is the value-weighted average of individual bond returns in a portfolio. Bonds in the portfolio with a high beta have high sensitivity to market returns and so stock market variables should contribute more to the forecast of these bond returns. Similarly, we use expected default frequency to sort bonds into five EDF portfolios. As bonds in the portfolio with high EDF have high default risk, stock market variables are likely to contain more information for these bonds. Conversely, bonds in the portfolio with low EDF have low default risk and so Treasury market variables are likely to contain more information for these safe bonds.

Table IA6 reports results of out-of-sample forecasts using the IWC predictor for each portfolio formed by the rating, beta and EDF. The percentage measure is the ratio between the out-of-sample R^2 of the IWC predictor using Treasury market variables only and the out-of-sample R^2 of the IWC predictor using all variables. Results strongly suggest that Treasury market variables play a much more important role for the bonds that have a high rating (e.g., AAA), low default risk and low beta. The ratios of the out-of-sample R^2 of the IWC predictor using Treasury market variables to that of the IWC predictor using all variables have the highest value for these bonds. Conversely, the ratios are the lowest for junk bonds and bonds with high EDF and betas. Results support the hypothesis that Treasury market variables are better predictors for safe bonds, and stock and other market variables are better predictors for risky bonds. Thus, Treasury and other market variables track different components of expected returns for different types of bonds. For high-quality bonds, Treasury market variables track the term or maturity premium which is the main component of expected returns of these safe bonds. For low-quality bonds, stock and corporate bond market variables track the credit risk premium which is the dominant component of expected returns for these risky bonds. The result also clearly indicates that premia of bonds with varying quality contain different components which behave distinctly. On the flip side, premia of different rated bonds should contain different information. To the extent that credit risk spreads convey important information for the real economy, the premium of low-quality bonds is likely to provide a more credible signal for business cycles and future economic activity.

[Insert Table IA6 here]

B.5 Multiple regressions

Recall that altogether we have 27 predictors of three types: stock, Treasury and corporate bond market variables. In this subsection, we examine how well each set of variables fares against others in multiple regression *vis-a-vis* IWC models in terms of out-of-sample forecasting performance.

We consider four multiple regression models using different sets of predictors in a horse race: (1) stock market variables; (2) Treasury market variables; (3) corporate bond market variables; and (4) all variables. The first two models enable us to see the economic relationship between corporate bond returns and variables in the stock and Treasury markets. If Treasury (stock) market variables forecast AAA (junk) bonds better, the traditional multivariate regression should naturally reveal this relationship. The remaining models give additional information about the role of corporate bond market variables as well as important variables in all three markets.

We perform out-of-sample forecasts of these multiple regression models and compare their performance with that of the IWC model in terms of R^2. Table IA7 reports the improvement of the IWC model over each multiple regression model. The improvement by the IWC is quite substantial across models. For example, in column 1, the IWC model outperforms the multiple regression model using stock market variables by 19.85 percent for the sample including all bonds. Column 2 shows the improvement of the IWC over the multiple regression model that includes only Treasury bond market variables. Results show that the improvement is much higher for speculative-grade bonds than for AAA bonds. Using only Treasury market variables as predictors thus underestimates the predictability of returns more for low-grade bonds than for high-grade bonds. The results of multiple regressions also confirm that Treasury market variables forecast the return of AAA bonds much better than that of junk bonds, and stock market variables provide better forecasts for junk bonds, consistent with the finding in Table IA6. Column 3 shows that the improvement of the IWC over the model with corporate bond market variables is fairly even across ratings suggesting that corporate bond market variables are important predictors across ratings.

A more surprising finding is in column 4 which uses all variables in the multiple regression. Consistent with the finding of Welch and Goyal (2008), this "kitchen sink" model performs much worse than other multiple regression models using only a subset of variables. As demonstrated by Rapach, Strauss and Zhou (2010), the "kitchen sink" model performs worse because each variable contains noise or false signals and the compounded errors from a large number of predictors can seriously compromise the model's forecasting ability for asset returns. Hence, it is suboptimal to include all variables in the multiple regression model. Our results for corporate bond returns confirm this prediction. As shown, the out-of-sample R^2s are considerably lower for the "kitchen sink" model by a large margin of 32 to 43 percent across ratings compared to the IWC forecasts.

[Insert Table IA7 about here]

B.6 Predictability on hedged returns and index returns

A potential concern is that corporate bond returns are predictable because the variables used in our model largely forecast the term structure, and the riskfree (Treasury) bond return is a major component of the corporate bond return. In this subsection, we address this issue by directly forecasting the hedged return in which we control for the return on US Treasuries over the same maturity window. In essence, the hedged (excess) return is simply the return compensating investors for taking credit risk. Moreover, we conduct forecasts using indexes of corporate bond returns to compare with the results we have so far based on portfolios of individual bond returns for robustness.

To calculate the hedged return, we first obtain the price of the equivalent bond that has the same coupon and maturity as the corporate bond by discounting the coupons with the Treasury spot rates matching the time of each coupon and the principal payment. The spot rates are taken from Gurkaynak, Sack and Wright (2007). We then subtract the return of this riskless equivalent bond from the return of corporate bond to generate the hedged return. Specifically, the hedged return is simply the return of the portfolio with a long position in the corporate bond and a short position in a riskfree bond that has the same coupon and maturity as the corporate bond. For the return based on the index, we calculate the excess bond return by taking the difference between the Barclays corporate bond index return and the one-month Treasury bill rate. The sample period of Barclays corporate bond index returns is from January 1987 to June 2012 for junk bonds and from August 1988 to June 2012 for other ratings, and out-of-sample forecasts start from January 1998.

Table IA8 reports the results of in- and out-of-sample forecasts based on the hedged returns of corporate bonds and excess returns of bond indexes. The upper panel reports the results for portfolios of individual bonds and the lower panel reports results for index excess returns. Results continue to show that the IWC has high predictive power for hedged returns. Thus, the predictive power of the model for the corporate bond return is not derived from its predictive power for the Treasury return. The IWC model once again outperforms the FF model considerably both in- and out-of-sample. The lower panel of Table IA8 reports the in- and out-of-sample results of index excess return forecasts. Results show that the IWC model performs quite well compared to the FF model. The improvement by the IWC forecasts increases as the rating decreases. The in- and out-of-sample R^2 of the IWC are all substantially higher than those for the FF model. Thus, the iterated combination forecast model appears to perform equally well for the index returns compiled by Barclays.

[Insert Table IA8 about here]

B.7 Economic regimes

Fama and French (1989) suggest that during economic downturns, income is low and so expected returns on corporate bonds should be high in order to provide an incentive to invest. In general, heightened risk aversion when economic conditions are poor demands a higher risk premium, thereby generating risk premium predictability. Consistent with this hypothesis, Rapach, Strauss and Zhou (2010) find that the predictability of stock returns varies with business conditions and risk premium forecasts are closely related to business cycles. Particularly, out-of-sample gains for the market risk premium forecast are tied to business conditions and tend to be greater when business conditions are poorer.

In light of the literature, we examine the predictability of corporate bond returns over periods with different rates of economic growth. Following Rapach, Strauss and Zhou (2010), we sort the sample period based on the real GDP growth rates and divide them into good, normal and bad growth periods using the top, middle and bottom third sorted real growth rates, and then examine the performance of the IWC in terms of out-of-sample R^2s.

Table IA9 reports the results of the out-of-sample performance during “good”, “normal” and “bad” growth periods between 1983 and 2012. Results show that return predictability is much stronger during the low-growth period than during the high-growth period.[4] This pattern is consistent with the findings of Rapach, Strauss and Zhou (2010) and Henkel, Martin and Nardari (2011) that stock returns are much more predictable during “bad” growth periods. Hence, it appears that across stocks and bonds, the return predictability is driven by the same fundamental forces such as financial constraints and changing business conditions and risk aversion. Table IA9 further shows that the discrepancy in the predictability between bad and good economies widens for long-maturity lower-quality bonds which have higher exposure to business cycle.

[Insert Table IA9 about here]

[4]Unreported results show that similar results hold for Treasury bond returns in different economic regimes.

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Table IA1. Summary statistics of predictors

This table reports the summary statistics of the predictors: the dividend-price ratio (D/P), dividend yields (D/Y), the earnings-price ratio (E/P), the dividend-payout ratio (D/E), stock variance (SVAR), the book-to-market ratio (B/M), net equity expansion (NTIS), S&P 500 index return (S&P500), aggregate leverage ratios (LEV1 and LEV2), effective cost (EC), Pastor-Stambaugh stock liquidity (PSS), Amihud stock liquidity (AmS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), inflation rate (INFL), CP 5-year factor (CP5), CP 10-year factor (CP10), percentage changes in the money market mutual fund flow (ΔMMMF), on-/off-the-run spread (Onoff), default yield spread (DFY), default return spread (DFR), issuance quality index (IQ), debt maturity index (DM) and portfolio yield spread (PYS) computed as the the mean yield spread of 20 corporate bond portfolios under investigation. ρ (1) and ρ (12) are the autoregressive coefficients at lag 1 and 12 of monthly intervals. The sample period is from January 1973 to June 2012.

	Predictor	Obs.	Mean	Std.	ρ (1)	ρ (12)
Stock market variables	D/P	474	-3.60	0.45	0.99	0.92
	D/Y	474	-3.59	0.45	0.99	0.92
	E/P	474	-2.81	0.51	0.99	0.69
	D/E	474	-0.79	0.35	0.98	0.2
	SVAR (%)	474	0.26	0.51	0.46	0.03
	B/M (%)	474	50.11	29.8	0.99	0.93
	NTIS (%)	474	0.92	1.99	0.97	0.48
	S&P 500 (%)	474	0.89	4.56	0.04	0.07
	LEV1 (%)	474	38.41	4.05	0.96	0.55
	LEV2 (%)	474	43.47	6.52	0.98	0.75
	EC	396	-0.01	0.22	0.04	0.19
	PSS	474	0.00	0.06	0.00	-0.02
	AmS	456	0.00	0.21	-0.02	0.06
Treasury market variables	TBL (%)	474	5.37	3.30	0.99	0.84
	LTY (%)	474	7.43	2.59	0.99	0.90
	LTR (%)	474	0.77	3.16	0.05	0.00
	TMS (%)	474	2.07	1.54	0.95	0.48
	INFL (%)	474	0.36	0.38	0.62	0.46
	CP 5-year (%)	474	1.33	1.81	0.77	0.45
	CP 10-year (%)	474	1.92	4.01	0.90	0.50
	ΔMMMF (%)	463	2.00	5.04	0.69	0.23
	Onoff (Bps)	474	2.18	22.90	0.18	0.03
Corporate bond market variables	DFY (%)	474	1.12	0.48	0.96	0.44
	DFR (%)	474	-0.02	1.47	-0.04	-0.02
	IQ (%)	426	-25.49	21.29	0.97	0.41
	DM (%)	474	-61.43	7.40	0.99	0.96
	PYS (%)	474	3.04	1.65	0.81	0.37

Table IA2. Sample distribution and summary statistics

This table reports the sample distribution of the corporate bond data (Panel A) and the summary statistics by rating and maturity (Pane B). The data are merged from different sources: the Lehman Brothers Fixed Income (LBFI) database, Datastream, the National Association of Insurance Commissioners (NAIC) database, the Trade Reporting and Compliance Engine (TRACE) database, and Mergent's Fixed Investment Securities Database (FISD). The combined corporate bond data are from January 1973 to June 2012. In each month, all bonds are sorted into five rating portfolios and then four maturity portfolios. The cut-off values for maturity portfolios are 5 years, 7 years, and 10 years.

Panel A. Sample distribution

Maturity	AAA	AA	A	BBB	Junk	All
			Distribution by maturity			
3	11,471	26,152	46,956	18,683	11,679	114,941
4	8,480	21,357	39,053	17,398	9,318	95,606
5	8,454	20,010	36,261	17,396	8,551	90,672
6	5,109	12,384	24,539	13,510	7,622	63,164
7	5,339	11,360	24,128	14,235	8,252	63,314
8	4,876	9,000	20,012	11,799	6,119	51,806
9	4,514	8,789	20,971	13,527	5,468	53,269
10	4,161	8,235	20,843	15,114	5,382	53,735
>10	11,818	25,981	70,031	62,598	24,050	194,478
All	64,222	143,268	302,794	184,260	86,441	780,985
			Distribution by data source			
Datastream	8,326	25,613	41,863	50,450	21,234	147,486
LBFI	15,539	42,180	115,257	65,312	23,533	261,821
NAIC	25,851	14,699	39,085	22,475	8,505	110,615
TRACE	14,506	60,776	106,589	46,023	33,169	261,063
All	64,222	143,268	302,794	184,260	86,441	780,985

Panel B. Summary statistics by rating and maturity

		Equal weighted			Value weighted		
Rating	Maturity	Excess return	S.D.	Corr. with equity	Excess return	S.D.	Corr. with equity
	All	0.26	1.84	0.25	0.26	1.73	0.22
AAA	Short	0.21	1.21	0.26	0.21	1.18	0.21
	Long	0.36	2.92	0.23	0.38	2.95	0.21
	All	0.27	1.76	0.33	0.26	1.68	0.31
AA	Short	0.24	1.24	0.33	0.21	1.19	0.31
	Long	0.40	2.54	0.29	0.39	2.55	0.27
	All	0.28	1.89	0.35	0.30	1.84	0.35
A	Short	0.25	1.38	0.34	0.24	1.36	0.33
	Long	0.40	2.64	0.33	0.41	2.64	0.34
	All	0.36	2.13	0.36	0.37	1.92	0.37
BBB	Short	0.31	1.73	0.34	0.33	1.54	0.35
	Long	0.45	2.90	0.32	0.39	2.89	0.34
	All	0.52	2.13	0.44	0.62	2.30	0.45
Junk	Short	0.35	2.16	0.34	0.48	2.29	0.38
	Long	0.75	2.67	0.44	0.90	3.19	0.41
	All	0.32	1.81	0.37	0.31	1.63	0.32
All	Short	0.27	1.31	0.36	0.25	1.15	0.30
	Long	0.45	2.50	0.35	0.44	2.31	0.30

Table IA3. In-sample R-squares of individual predictors and covariance of predictors with corporate bond excess returns

This table reports the in-sample univariate regression R-squares of various predictors (the left panel), and estimates of the covariances of standardized individual predictors with the excess returns of rating portfolios and the portfolio (All) that includes all bonds (the right panel). The boldfaced figures indicate significance at least at the 10% level. The sample period is from January 1973 to June 2012.

	In-sample R-squares of individual predictors												Covariance of predictors with corporate bond excess returns											
	Monthly (%)						Quarterly (%)						Monthly (%)						Quarterly (%)					
Predictor	AAA	AA	A	BBB	Junk	All	AAA	AA	A	BBB	Junk	All	AAA	AA	A	BBB	Junk	All	AAA	AA	A	BBB	Junk	All
D/P	0.10	0.19	0.00	0.05	0.01	0.07	0.33	0.42	0.00	0.07	0.06	0.20	-0.05	-0.07	-0.01	-0.04	0.03	-0.04	-0.06	-0.07	0.00	-0.03	0.03	-0.04
D/Y	0.21	0.26	0.00	0.02	0.04	0.13	0.55	0.61	0.01	0.09	0.04	0.33	-0.07	-0.08	-0.01	-0.02	0.04	-0.05	-0.08	**-0.08**	-0.01	-0.04	0.03	-0.06
E/P	0.23	1.80	1.23	1.83	2.48	0.60	0.48	3.67	2.36	3.51	3.98	1.19	-0.08	**-0.20**	**-0.18**	**-0.24**	**-0.33**	**-0.12**	-0.07	**-0.20**	**-0.18**	**-0.23**	**-0.28**	**-0.11**
D/E	0.09	1.80	2.25	2.66	5.67	0.59	0.08	3.64	4.66	5.46	10.20	1.05	**0.05**	**0.20**	**0.25**	**0.29**	**0.51**	**0.12**	0.03	**0.20**	**0.25**	**0.29**	**0.45**	**0.10**
SVAR	1.36	2.16	1.94	1.05	1.21	1.34	2.19	5.77	4.19	3.58	4.55	2.97	**0.19**	**0.22**	**0.23**	**0.18**	**0.23**	**0.17**	**0.16**	**0.25**	**0.24**	**0.23**	**0.30**	**0.17**
B/M	0.24	0.61	0.18	0.39	0.25	0.35	0.59	1.26	0.29	0.71	0.41	0.74	-0.08	**-0.12**	-0.07	-0.11	-0.11	-0.09	**-0.08**	**-0.12**	-0.06	**-0.10**	-0.09	**-0.09**
NTIS	1.12	0.65	0.52	0.21	0.50	0.83	2.08	1.26	0.59	0.39	0.59	1.45	**-0.17**	**-0.12**	-0.12	-0.08	-0.15	**-0.14**	**-0.15**	**-0.12**	**-0.09**	**-0.08**	**-0.11**	**-0.12**
S&P 500	1.74	0.45	0.00	0.86	0.74	0.64	2.77	1.38	0.52	0.02	0.04	1.54	**-0.21**	-0.10	0.00	**0.17**	**0.18**	**-0.12**	**-0.18**	**-0.12**	-0.08	-0.02	-0.03	**-0.13**
LEV1	0.28	0.94	1.04	0.67	1.56	0.44	0.20	1.67	2.15	1.69	3.14	0.63	0.09	**0.15**	**0.17**	**0.15**	**0.27**	0.10	0.05	**0.13**	**0.17**	**0.16**	**0.25**	**0.08**
LEV2	1.85	3.21	3.01	3.90	5.60	2.74	3.06	5.92	5.09	8.15	10.47	5.14	**0.22**	**0.27**	**0.29**	**0.35**	**0.50**	**0.25**	**0.19**	**0.25**	**0.27**	**0.35**	**0.46**	**0.23**
EC	0.49	0.85	0.80	0.45	1.21	0.64	0.35	0.87	0.76	0.72	1.30	0.61	0.12	**0.14**	**0.15**	0.11	**0.21**	0.12	0.07	**0.10**	**0.10**	**0.10**	**0.15**	0.08
PSS	0.01	0.39	0.29	0.84	0.93	0.23	0.40	0.14	0.09	0.03	0.06	0.17	-0.02	-0.09	-0.09	**-0.16**	**-0.21**	-0.07	0.07	0.04	0.04	-0.02	0.03	0.04
AmS	0.13	0.25	0.34	0.00	0.01	0.11	1.14	0.59	0.43	0.07	0.22	0.70	0.06	0.08	0.10	0.00	-0.03	0.05	**0.11**	0.08	0.08	0.03	0.07	**0.09**
TBL	0.76	1.72	1.16	2.47	2.56	1.42	0.99	2.63	1.51	3.98	3.94	2.07	**-0.14**	**-0.20**	**-0.18**	**-0.28**	**-0.34**	**-0.18**	**-0.11**	**-0.17**	**-0.14**	**-0.25**	**-0.28**	**-0.15**
LTY	0.09	0.30	0.05	0.37	0.61	0.18	0.00	0.15	0.01	0.24	0.49	0.03	-0.05	-0.08	-0.04	-0.11	**-0.17**	-0.06	0.00	-0.04	0.01	-0.06	-0.10	-0.02
LTR	5.29	4.53	4.47	5.95	4.27	5.83	0.65	0.74	0.52	1.04	0.76	1.14	**0.37**	**0.32**	**0.35**	**0.44**	**0.44**	**0.36**	**0.09**	**0.09**	**0.09**	**0.13**	**0.12**	**0.11**
TMS	1.95	3.67	3.82	5.61	4.61	3.47	4.83	8.15	7.94	12.05	9.60	7.94	**0.23**	**0.29**	**0.32**	**0.42**	**0.46**	**0.28**	**0.23**	**0.29**	**0.33**	**0.43**	**0.44**	**0.28**
INFL	0.76	2.30	1.52	2.27	2.55	1.97	0.54	2.68	1.87	2.63	4.32	1.95	**-0.14**	**-0.23**	**-0.20**	**-0.27**	**-0.34**	**-0.21**	**-0.08**	**-0.17**	**-0.16**	**-0.20**	**-0.29**	**-0.14**
CP5	1.17	2.02	2.37	2.65	1.61	1.97	3.56	5.25	5.52	6.06	4.77	5.68	**0.18**	**0.21**	**0.25**	**0.29**	**0.27**	**0.21**	**0.20**	**0.24**	**0.28**	**0.30**	**0.31**	**0.24**
CP10	2.32	3.30	2.92	2.93	2.17	3.23	6.25	6.98	6.36	6.18	4.87	7.83	**0.25**	**0.27**	**0.28**	**0.31**	**0.31**	**0.27**	**0.27**	**0.27**	**0.30**	**0.31**	**0.31**	**0.28**
ΔMMMF	1.24	2.10	2.55	3.06	1.79	2.10	1.73	3.28	3.96	4.92	3.23	3.14	**-0.18**	**-0.22**	**-0.26**	**-0.31**	**-0.29**	**-0.22**	**-0.14**	**-0.19**	**-0.23**	**-0.28**	**-0.26**	**-0.18**
Onoff	5.60	5.95	5.85	6.11	5.94	6.70	1.61	2.46	2.09	2.97	2.89	2.85	**0.38**	**0.37**	**0.40**	**0.44**	**0.52**	**0.39**	**0.13**	**0.16**	**0.17**	**0.21**	**0.24**	**0.17**
DFY	0.23	1.23	2.03	2.38	2.41	0.89	0.18	2.08	3.52	4.10	3.65	1.18	0.08	**0.17**	**0.23**	**0.28**	**0.33**	**0.14**	0.04	**0.15**	**0.22**	**0.25**	**0.27**	**0.11**
DFR	0.91	0.03	0.01	0.59	0.13	0.28	0.38	0.04	0.00	0.21	0.37	0.14	**-0.15**	-0.03	-0.02	**0.14**	0.08	-0.08	-0.07	-0.02	0.00	0.06	0.09	-0.04
IQ	0.00	0.14	0.32	0.16	0.43	0.03	0.01	0.29	0.68	0.33	0.97	0.05	0.00	0.06	0.10	0.07	0.14	0.02	-0.01	0.06	0.10	0.07	**0.14**	0.02
DM	0.12	0.34	0.21	0.87	0.89	0.23	0.14	0.47	0.21	1.39	1.25	0.31	-0.06	-0.09	-0.08	**-0.17**	**-0.20**	-0.07	-0.04	-0.07	-0.05	**-0.15**	**-0.16**	-0.06
PYS	0.75	2.79	3.28	5.18	6.88	2.91	3.57	9.41	10.58	14.78	15.80	8.95	**0.14**	**0.25**	**0.30**	**0.41**	**0.56**	**0.26**	**0.20**	**0.32**	**0.38**	**0.48**	**0.57**	**0.30**

Table IA4. Forecast encompassing tests
This table reports the *p*-values of the Harvey, Leybourne and Newbold (1998) statistics for the null hypothesis that the out-of-sample forecast of model 1 encompasses the out-of-sample forecast of model 2 for bonds of different ratings and maturities. The sample period is from January 1973 to June 2012, while the out-of-sample forecast starts from January 1983.

			Rating					
Maturity	Model 1	Model 2	AAA	AA	A	BBB	Junk	All
All	IWC	FF	0.23	0.33	0.42	0.38	0.51	0.33
	IWC	GH	0.38	0.51	0.71	0.68	0.45	0.74
	IWC	PCA	0.15	0.38	0.49	0.33	0.53	0.23
	FF	IWC	0.00	0.00	0.00	0.00	0.00	0.00
	GH	IWC	0.00	0.00	0.00	0.00	0.00	0.00
	PCA	IWC	0.00	0.00	0.00	0.00	0.00	0.00
Short (2 Yrs < Mat. < 5 Yrs.)	IWC	FF	0.05	0.20	0.43	0.48	0.31	0.12
	IWC	GH	0.25	0.63	0.75	0.85	0.29	0.60
	IWC	PCA	0.04	0.22	0.54	0.44	0.47	0.07
	FF	IWC	0.00	0.00	0.00	0.00	0.00	0.00
	GH	IWC	0.00	0.00	0.00	0.00	0.02	0.00
	PCA	IWC	0.00	0.00	0.00	0.00	0.00	0.00
	MC	IWC	0.00	0.00	0.00	0.00	0.00	0.00
5 Yrs < Mat. < 7 Yrs.	IWC	FF	0.33	0.17	0.32	0.15	0.30	0.23
	IWC	GH	0.34	0.29	0.52	0.36	0.28	0.61
	IWC	PCA	0.17	0.24	0.43	0.08	0.22	0.17
	FF	IWC	0.00	0.00	0.01	0.00	0.00	0.00
	GH	IWC	0.00	0.00	0.01	0.00	0.00	0.00
	PCA	IWC	0.00	0.00	0.00	0.00	0.00	0.00
7 Yrs < Mat. < 10 Yrs.	IWC	FF	0.08	0.18	0.22	0.05	0.52	0.19
	IWC	GH	0.08	0.32	0.40	0.30	0.87	0.42
	IWC	PCA	0.08	0.23	0.31	0.13	0.38	0.20
	FF	IWC	0.00	0.00	0.00	0.01	0.00	0.00
	GH	IWC	0.00	0.00	0.00	0.00	0.00	0.00
	PCA	IWC	0.00	0.00	0.00	0.00	0.00	0.00
Long (Mat. > 10 Yrs.)	IWC	FF	0.11	0.17	0.18	0.14	0.44	0.23
	IWC	GH	0.14	0.08	0.26	0.04	0.48	0.43
	IWC	PCA	0.14	0.26	0.29	0.08	0.59	0.19
	FF	IWC	0.03	0.01	0.03	0.01	0.01	0.00
	GH	IWC	0.02	0.01	0.02	0.05	0.02	0.00
	PCA	IWC	0.00	0.00	0.00	0.00	0.00	0.00

Table IA5. Forecasts with the extended models

This table reports out-of-sample R squares (R^2_{OS}) and utility gains of MC, WC, IMC, and IWC forecasts of the two extended models for the portfolio that includes all junk bonds (All) and portfolios of junk bonds with maturities from short to long. Model 1 has the GARCH (1,1) formulation

$$r_{t+1} = a_j + b_j z_{jt} + \varepsilon_{t+1,j},$$

where $\varepsilon_{t+1,j} \sim N(0, \sigma^2_{t+1,j})$, $\sigma^2_{t+1,j} = \gamma_{0,j} + \gamma_{1,j}\sigma^2_{t,j} + \gamma_{2,j}\varepsilon^2_{t,j}$. In Model 2, we impose the non-negative risk premium constraint and restrictions that the conditional Sharpe ratio is between zero and two in the spirit of Pettenuzzo, Timmermann and Valkanov (2014). The p-value of R^2_{OS} is based on the MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance levels of 1%, 5%, and 10%, respectively. The sample period is from January 1973 to June 2012, while the out-of-sample forecast starts from January 1983.

	$R^2_{OS}(\%)$				Utility gains (%)			
Maturity	MC	WC	IMC	IWC	MC	WC	IMC	IWC
				Model 1				
All	3.25^a	3.21^a	11.66^a	11.99^a	2.09	2.25	2.14	2.81
Short	2.80^a	2.73^a	9.46^a	9.48^a	1.50	3.34	2.01	3.67
5 Yrs<Mat<7 Yrs	2.41^a	2.38^a	6.69^a	6.53^a	1.25	2.96	1.98	2.93
7 Yrs<Mat<10 Yrs	3.53^a	3.49^a	9.40^a	9.41^a	1.44	5.48	2.39	5.59
Long	2.02^a	2.01^a	6.50^a	6.53^a	-0.53	-0.95	-0.52	-1.00
				Model 2				
All	3.10^a	2.93^a	11.87^a	11.70^a	1.86	1.80	1.71	2.11
Short	2.64^a	2.48^a	9.53^a	9.54^a	1.83	1.77	1.93	2.45
5 Yrs<Mat<7 Yrs	2.45^a	2.34^a	7.43^a	7.10^a	2.08	1.99	4.08	2.32
7 Yrs<Mat<10 Yrs	3.59^a	3.43^a	8.79^a	8.98^a	2.42	2.32	5.04	4.63
Long	1.98^a	1.90^a	7.54^a	7.14^a	-0.68	-0.68	-0.83	-0.48

Table IA6. Out-of-sample forecasts using the IWC of Treasury market variables

This table reports the out-of-sample R-squares (R^2_{OS}) of iterated weighted average combination (IWC) forecast using only Treasury market variables for each portfolio formed by rating, beta and EDF. The percentage measure is the ratio between the out-of-sample R-squares of the IWC using Treasury market variables only and that of the IWC using all variables including the Treasury, corporate bond and stock market variables. Beta is the stock market return beta and EDF is the expected default probability estimated from the Merton (1974) model. The statistical significance of R^2_{OS} is based on the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance level of 1%, 5%, and 10%, respectively. The sample period is from January 1973 to June 2012, while the out-of-sample forecast starts from January 1983.

		Monthly		Quarterly	
		R^2_{OS}	Percentage	R^2_{OS}	Percentage
Rating	AAA	5.76^a	108.36	3.57^b	62.33
	AA	8.10^a	81.53	9.59^a	61.49
	A	6.28^a	73.34	5.77^a	51.06
	BBB	6.64^a	68.62	7.19^a	47.08
	Junk	6.24^a	55.03	5.91^b	34.81
Beta	Low	8.23^a	102.99	6.54^a	59.66
	2	5.00^a	101.27	0.94^b	42.20
	3	6.25^a	100.17	3.90^b	39.57
	4	5.27^a	70.27	5.28^a	39.19
	High	2.91^a	48.74	3.36^b	36.47
EDF	Low	5.11^a	112.22	4.60^b	56.99
	2	7.64^a	83.78	6.73^b	43.84
	3	9.24^a	66.47	9.15^a	50.16
	4	4.93^a	69.73	3.25^b	50.47
	High	8.44^a	69.20	7.44^a	43.28

Table IA7. Comparisons between the IWC and multiple regression models

This table reports the difference between the results of the iterated weighted combination (IWC) and multiple regression models for the portfolio (ALL) that includes all bonds and portfolios by rating and maturity. We consider four multiple regression models: (1) the multiple regression model using stock market variables; (2) the model using Treasury market variables; (3) the model using corporate bond market variables; and (4) the kitchen sink model using all variables. Δ1, Δ2, Δ3, Δ4 measure the difference of out-of-sample R squares between the IWC and the above four models. The sample period is from January 1973 to June 2012, while the out-of-sample forecast starts from January 1983.

		Monthly(%)				Quarterly(%)			
Maturity	Rating	Δ1	Δ2	Δ3	Δ4	Δ1	Δ2	Δ3	Δ4
All	AAA	18.64	2.98	5.16	37.14	64.46	9.64	4.66	63.95
	AA	22.80	7.20	9.39	42.95	63.99	16.10	10.60	64.01
	A	17.51	7.15	9.33	31.94	55.14	12.60	10.30	56.56
	BBB	22.91	6.95	9.53	38.88	48.25	15.27	12.63	66.63
	Junk	21.77	10.35	8.88	34.73	30.77	17.49	8.69	35.58
	All	19.85	6.11	7.32	37.36	71.84	15.91	7.92	70.22
Short (2 Yrs < Mat. <5 Yrs)	AAA	13.52	2.29	6.20	32.52	68.57	8.73	7.00	77.26
	AA	19.07	9.21	11.94	37.37	60.80	17.53	14.19	77.11
	A	19.34	10.83	10.60	35.84	57.24	16.94	10.90	66.20
	BBB	17.70	10.06	10.40	31.36	35.72	17.02	14.09	60.40
	Junk	16.45	9.03	7.22	22.97	22.38	11.51	9.01	24.01
	All	17.32	7.06	8.24	35.47	70.66	16.73	9.85	75.56
5 Yrs< Mat. < 7 Yrs	AAA	13.52	1.75	3.64	23.64	67.09	7.02	6.41	72.64
	AA	17.11	8.11	7.57	30.07	61.94	15.59	9.25	70.25
	A	16.03	9.57	7.22	31.55	59.94	14.53	8.72	66.28
	BBB	20.37	8.39	5.57	43.31	64.48	17.39	7.09	81.02
	Junk	18.22	5.91	5.29	24.22	64.53	17.28	5.39	56.93
	All	18.72	7.10	6.03	35.53	77.52	18.09	7.29	76.89
7 Yrs < Mat. < 10 Yrs	AAA	19.49	1.34	2.03	31.63	76.16	9.36	-0.24	52.72
	AA	19.60	4.43	7.81	40.10	60.38	11.46	8.51	56.61
	A	16.94	5.03	8.09	32.58	63.72	11.55	8.40	65.54
	BBB	26.19	7.47	8.29	51.49	61.86	17.82	12.46	83.21
	Junk	24.60	4.76	7.73	43.37	33.25	14.53	7.23	56.51
	All	17.44	4.77	5.89	36.55	78.24	14.94	5.90	76.34
Long (Mat. > 10 Yrs)	AAA	12.80	4.49	2.06	27.50	52.01	6.05	3.04	53.22
	AA	19.51	3.42	5.39	38.63	64.12	12.60	7.21	51.09
	A	13.64	5.38	5.98	23.22	51.25	8.49	8.46	52.81
	BBB	19.25	17.09	4.10	46.60	66.70	24.31	8.13	91.04
	Junk	16.37	8.06	5.84	27.06	22.30	11.48	6.34	35.79
	All	21.37	4.55	5.36	39.71	67.34	10.59	7.23	56.48
Average		18.60	6.69	6.94	34.84	59.09	13.95	8.22	70.58

Table IA8. Forecasts of hedged returns and Barclays corporate bond index excess returns

This table reports the results of hedged returns and Barclays corporate bond index excess returns. The hedged return is the return from a long position in corporate bonds and a short position in a riskfree portfolio that has the same cash flow of the corporate bond. The price of riskfree portfolio is determined by its future cash flows discounted using the zero-coupon yield curve from Gurkaynak, Sack and Wright (2007). The Barclays corporate bond index excess return is the difference between the Barclays corporate bond index return and one month Treasury bill rate. The statistical significance of R^2_{OS} is based on the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance level of 1%, 5%, and 10%, respectively. For hedged returns, the sample period is from January 1973 to June 2012, while the out-of-sample forecast starts from January 1983. For Barclays corporate bond index excess returns, the sample period is from January 1987 to June 2012 for junk bonds and from August 1988 to June 2012 for other ratings, while out-of-sample forecasts start from January 1998. Results are reported for bonds of different ratings and the portfolio including all bonds (All).

		Monthly(%)			Quarterly(%)		
		FF	IWC	Δ	FF	IWC	Δ
		In-sample R squares					
	AAA	0.05	2.68	2.63	1.53	7.15	5.62
	AA	3.15	9.99	6.83	9.30	18.18	8.88
Hedged return	A	4.44	12.07	7.63	12.11	19.49	7.37
	BBB	3.92	15.06	11.14	13.06	20.60	7.54
	Junk	2.26	10.46	8.21	5.97	15.70	9.72
	All	2.60	9.44	6.84	8.79	16.86	8.07
		Out-of-sample R squares					
	AAA	-0.72	-1.16	-0.44	-1.98	0.50^a	2.48
	AA	1.66^c	4.46^a	2.80	4.54^a	6.51^a	1.98
Hedged return	A	1.32^c	4.88^a	3.56	4.33^a	7.18^a	2.85
	BBB	-0.05	4.93^c	4.98	5.31^a	7.68^a	2.37
	Junk	1.66^b	4.34^a	2.67	3.73^a	4.32^a	0.59
	All	-0.26	4.64^a	4.90	1.40^a	8.38^a	6.97
		In-sample R squares					
	AAA	1.04	6.75	5.71	3.68	9.54	5.86
Barclays corporate bond index excess return	AA	1.88	6.11	4.23	5.08	12.28	7.20
	A	2.83	6.57	3.74	6.40	12.65	6.25
	BAA	6.57	10.26	3.70	15.18	20.43	5.25
	Junk	4.04	15.97	11.93	11.90	21.21	9.31
	All	4.96	9.63	4.67	11.15	18.14	6.99
		Out-of-sample R squares					
	AAA	-2.22	-0.74	1.48	0.90^c	-1.30	-2.19
Barclays corporate bond index excess return	AA	-0.60	0.11^c	0.71	1.49^b	5.04^a	3.55
	A	1.32	2.25^b	0.93	2.11^b	5.31^a	3.19
	BAA	6.65^a	8.37^a	1.72	13.09^a	16.91^a	3.82
	Junk	3.66^a	8.58^a	4.92	5.53^a	12.56^a	7.04
	All	3.98^b	7.02^a	3.04	9.48^a	15.87^a	6.38

Table IA9. Out-of-sample forecasts under different economic regimes

This table reports the out-of-sample R-squares of monthly return forecasts using the IWC approach during good, normal and bad growth periods for the portfolio (All) including all bonds and portfolios by rating and maturity. The statistical significance of R^2_{OS} is based on the *p*-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance levels of 1%, 5%, and 10%, respectively. The sample period is from January 1973 to June 2012, while the out-of-sample forecast starts from January 1983.

Maturity	GDP	AAA	AA	A	BBB	Junk	ALL
	Good	4.16^a	3.44^a	4.60^b	4.19^b	6.39^b	3.50^a
All	Normal	6.23^a	13.53^a	13.73^a	16.38^a	15.28^a	12.12^a
	Bad	6.19^a	14.06^b	8.85^a	9.98^a	11.77^a	9.59^a
	Good	5.03^a	5.01^a	9.04^b	6.45^b	3.17^b	4.67^a
Short	Normal	3.77^a	13.40^a	11.31^a	25.43^a	19.71^a	10.03^a
	Bad	5.02^a	17.53^a	11.49^a	9.07^a	7.98^a	8.30^a
	Good	5.97^b	4.06^a	3.84^b	1.75^b	3.69^c	4.07^b
5Yrs<Mat.<7Yrs	Normal	2.90^b	10.82^a	9.32^a	15.68^a	16.91^a	10.02^a
	Bad	6.45^a	11.23^a	10.56^a	6.57^b	3.74^a	7.99^a
	Good	3.60^b	3.44^a	4.81^c	3.95^b	3.22^b	3.36^b
7Yrs<Mat.<10Yrs	Normal	3.14^a	13.79^a	15.14^a	11.99^a	20.07^a	14.17^a
	Bad	2.97^b	9.39^b	5.28^a	9.42^a	6.88^a	5.92^b
	Good	-0.26	4.24^c	0.27^c	0.75^b	2.75^b	2.33^b
Long	Normal	5.98^a	10.96^a	14.25^a	6.75^a	14.24^a	11.88^a
	Bad	1.79	3.01^b	3.04	9.90^c	5.32^b	3.95^b

Figure IA1. Bond cumulative returns
This graph plots the cumulative excess returns of rating portfolios and Barclays indicies.