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Cyclicality in the Prices of Risk: What More Can We Learn from Explainable AI?

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Abstract

We uncover the temporal patterns of the prices of risk through industry portfolios with varying sensitivities to the economic and financial cycles. Conditioning on the highs and lows of the cycles is key for statistical significance of the intertemporal component. Unlike market risk, its price decreases during an economic downturn but increases under tight funding conditions. Predictive machine learning models and their SHAP values suggest that a limited number of firm characteristics convey the most informative signals about asset risk premia. Valuation ratios are more important determinants for Cyclical relative to Defensive industries, whereas Return characteristics become crucial during recessions.

Keywords: Intertemporal CAPM, Hedging Demand, Business Cycle, Explainable AI

JEL classification: G11, G12.

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1 Introduction

Prices of risk in financial markets change through the economic and financial cycles as a result of a variety of factors. As conditions evolve over time, so do the perception of risk and market sentiment, resulting in, for example, higher risk appetite and lower risk premiums in economic booms. In these periods, companies tend to report strong(er) earnings, which further incentivizes risk-taking and lowers the prices of risk. The variation in the economic environment also triggers central banks' reaction to changing interest rates, which in turn alters demand for assets and risk prices.

The analysis of the risk-return trade-off, however, has represented a challenge for the empirical asset pricing literature. For instance, the magnitude of the price of the market risk, its statistical significance, and even its sign have been largely debated. A number of possible explanations have been put forward for the conflicting evidence, mostly attributing those findings to the omission of some factors in the pricing equation. Indeed from a theoretical standpoint, going back to Merton (1973)'s seminal paper, expected returns depend on compensation for bearing market risk as well as on the intertemporal hedging demand related to additional factors which proxy for changes in the investment opportunity set. Although the empirical investigation of the role of the intertemporal risk factor on asset prices is now quite extensive, less is known about the dynamics of the compensation for these risk factors through states of the economy.[1] Moreover, what drives the dynamics of expected returns and which ones among the large number of firm characteristics gain investors' attention in the evolving economic environment is not well understood.

We contribute to this strand of literature by investigating the behavior of the prices of intertemporal risk through the economic and financial cycles with the help of industry portfolios. As we intend to capture investors' assessment of changing investment opportunities in the economy, we employ a fully conditional ICAPM framework and examine the dynamics in the expected compensation for risk. We adopt and expand the methodology of Bali and Engle (2010) who use time-varying conditional covariances of assets with risk factors, generated separately, to estimate

[1] See, among others, Whitelaw (2000), Scruggs and Glabadanidis (2003), Brennan, Wang, and Xia (2004), Ang, Hodrick, Xing, and Zhang (2006b), Gerard and Wu (2006), Guo (2006), Hahn and Lee (2006), Petkova (2006), Guo and Whitelaw (2006), Bali (2008), Guo and Savickas (2008), Bollerslev, Tauchen, and Zhou (2009), Chen and Zhao (2009), Ozoguz (2009), Bali and Engle (2010), Bollerslev and Todorov (2011), Wachter (2013), Gagliardini, Ossola, and Scaillet (2016), Barroso, Boons, and Karehnke (2021).

the risk-return trade-off within a panel regression. In our implementation, we also incorporate the impact of investors' information set on the estimation of the conditional prices of risk. The specification of our empirical asset pricing model is thus internally consistent in the sense that it is both conditional and intertemporal.

Although our goal is to capture the dynamics of the risk-return trade-off in the time series, we gain power with the help of a large cross-section as we constrain the coefficients in estimating the prices of risk. To this aim, and to control for strong factor structure in the test assets (Lewellen, Nagel, and Shanken, 2010), we choose to study 49 industry portfolios, which are exposed to various economic shocks and thus perform differently through the business cycle. We follow previous research in selecting the empirical proxies that capture the risk from shifts in investment opportunities, investigating the role of long-term bond returns and innovations in variables associated with the macroeconomic environment as intertemporal risk factors. We analyze their contribution to the prices of risk from 1986 to 2022, covering the past four NBER recessions, and cross-check our findings with even a longer sample of the last 61 years, albeit with a smaller cross-section of assets and conditioning variables. In a subsequent step, we use a host of advanced machine learning techniques, in a framework similar to Gu, Kelly, and Xiu (2020), to discriminate among a large number of firm characteristics and to understand how they drive the compensation for the postulated risk factors through the economic and related financial cycle.

Differently from the reward for market risk, we find that the reward for intertemporal risk is significant only over ranges of the distribution of the conditioning information variable which correspond to distinct phases of the cycles. For instance, the risk prices of the long-term Bond or of changes in Default Premium, two proxies that negatively correlate with the market portfolio returns, are estimated as positive and significant when the aggregate dividend yield is below its mean. However, as the dividend yield increases, say during the recession periods, the economic and statistical importance of these risk factors decrease. Over this range, we instead observe an opposite trend and statistical significance for the changes in Term Spread, which on average correlates positively with the market portfolio. Conditioning on other financial variables, such as the TED spread or the VIX index, we find that the price of intertemporal risk is heightened in periods when investors' funding liquidity dries up or when their risk appetite decreases. On the other hand, we show that conditioning information is not crucial to finding support for market risk.

With the full information set, we find that the estimated time-varying price of market risk is increasingly positive in the recession patterns of the conditioning variables. Even more interesting are the dynamics of the intertemporal risk prices. The risk price for the innovations in the Term Spread is increasing while the prices for the long-term Bond and innovations in the Default Premium are decreasing during the recession periods compared to the expansions. Taking into consideration that most of the intertemporal risk proxies have negative covariances with the assets, that also become larger during bad times, the evidence overall suggests that the risk prices generate a negative component in the asset total risk premia. Analyzing the contribution of each risk factor, we show that the share of intertemporal risk is substantial, accounting overall for almost half of the total risk premia, with the innovations in Default Premium the most relevant of the intertemporal factors. Through the business cycle, we find that the share of market risk relatively increases while that of intertemporal risk decreases during recessions. In the cross-section, market risk contributes more to the Cyclical industries' risk premia, whose sales are more heavily affected during recessions. Conversely, the intertemporal risk factors such as changes in Term Spread or in Default Premium contribute relatively more to the risk premia of the firms in the Defensive sectors.

The time variation in the relationship between expected returns and risk through the cycles is thus in line with our intuition from the intertemporal pricing model that the increasing likelihood of bad times leads to revisions in investors' risk assessment about the future. It is also consistent with the empirical evidence from the predictability literature going back to Ferson and Harvey (1991), which suggests that the required reward for risk varies with the information about economic conditions that is publicly available to investors. With the help of a cross-section of assets exhibiting different correlations with the economy and the market, we further show that conditioning information is even more important in identifying significant intertemporal risk. Overall the evidence strongly indicates that accounting for the variation through the highs and lows in the economic and financial cycles is a key aspect of capturing such component.

In the second part of the paper, we discriminate among a large number of firms' characteristics to identify the important determinants and rank the extent of their association with the estimated risk premia. We exploit the information content of 73 characteristics, across nine categories covering topics such as firms' financial performance, liquidity, solvency, valuation, and profitability, as well as their capital structure and efficient use of resources. Previous asset pricing research shows that some of these characteristics are informative about firms' fundamental values and changes in their stock price.[2] In our analysis, we adopt a machine learning approach suitable to high-dimensional settings due to issues related to dimensionality, multicollinearity, and nonlinearity that are pervasive in these data. For our purpose, we exploit recent developments in the field of Explainable Artificial Intelligence, specifically the use of SHAP value (Lundberg and Lee, 2017).[3] SHAP is a unified framework for explaining the output of machine learning models and responds to some of their shortcomings. In fact, although advanced machine learning techniques generally outperform linear models in fitting the data (see, for example, Gu et al., 2020 and Akbari, Ng, and Solnik, 2021), they often provide little intuition of the underlying structural relationship between the explanatory variables and the dependent variable. Instead, SHAP values provide a fair and consistent way to attribute the contribution of a feature to the predicted outcome, both in comparison to other features and to a specific point over the range of the time sample, even in the presence of feature interactions and dependencies.

Our feature attribution analysis reveals that the Return and Valuation categories become particularly important during the recession periods. For instance, the calculated SHAP values for the firms' volatility and Shiller's Cyclically Adjusted P/E ratio increase by 135.5% and 139.9%, making them the most important feature of our set in bad times. Changes in investors' risk appetite, their loss aversion, and their attention to the downside risk might be the underlying mechanism for this finding (Ang, Chen, and Xing, 2006a; Bollerslev, Patton, and Quaedvlieg, 2022). In addition, P/E ratios point to the importance of corporate sales, whose variation results in profit swings during the business cycle. In line with their SHAP values associated with the expected returns, the magnitude of those characteristics also changes significantly during recession periods. On average in our sample, firms are 87.4% more volatile and record 19.8% less P/E ratios at these times.

When we focus on differences across Cyclical and Defensive sectors, whose sales deviate the most in the business cycle, our analysis suggests that Return and Valuation features are indeed the most impactful determinants for the risk premia. The SHAP values for firms in those sectors vary the most across these categories; Return category SHAP values are 3.452 point estimates

[2] See for example, Bhandari (1988), Campbell and Shiller (2001), Chen and Zhang (2007), Soliman (2008), Ball, Gerakos, Linnainmaa, and Nikolaev (2016), Medhat and Schmeling (2022).

[3] SHAP stands for SHapley Additive exPlanations. The concept of SHAP values is rooted in the Shapley value in cooperative game theory, where the marginal contribution of each player to each game output is measured.

larger for Defensive sector firms and the Valuation SHAP values are 2.682 point estimates larger for Cyclical ones. These are meaningful metrics. In fact, the difference between any two sectors in any feature category SHAP values is smaller than the values above. Financial Soundness matters for both. However, features of the Return category are more important determinants than those of the Efficiency category for Defensive industries, with the opposite for the Cyclical industries. If investors' demand for defensive stocks is driven by the hedging that they provide against economic downturns, then investors are expected to pay more attention to the risk profiles of these firms. This is consistent also with our findings that firms' volatility and payables turnover ratio are much more important features for those firms compared to the Cyclical ones. The contribution of this analysis is in helping investors sort through the large number of signals conveyed by these characteristics, differentiating across the economic and financial cycles and across sectors.

The remainder of the paper is organized as follows. Section 2 presents the empirical model and the estimation methodology. The data description is in Section 3. The analysis of the price of risk through time and feature contribution to the estimated risk premia are discussed in Sections 4 and Section 5. Section 6 concludes.

2 Empirical Methodology

2.1 Asset pricing specification

Theoretical intertemporal risk models show that in a dynamic economy, investors are compensated in equilibrium for the contemporaneous exposure of their portfolio to market risk, as well as to the risk of future shifts in the investment opportunity set (see Merton, 1973; Campbell, 1993). This is the result of the hedging demands of forward-looking investors who anticipate stochastic changes in investment opportunities and yearn to achieve smooth consumption through time and possible states of nature. In these models, the general relationship between asset returns is governed by the following intertemporal asset pricing model (ICAPM):

$$E_{t-1}\left[R_t - r_{f,t-1}\right] = \lambda_t \mathrm{Cov}_{t-1}\left(R_t, r_{m,t}\right) + \boldsymbol{\gamma}_t' \mathrm{Cov}_{t-1}\left(R_t, Z_t\right) \tag{1}$$

Where $r_{f,t}$ is the risk-free rate, R_t is a vector of N asset returns (each denoted by $r_{i,t}$), $r_{m,t}$ is the market return and Z_t are the L state variables (each denoted by $z_{j,t}$) that predict changes in the future investment opportunity set, all computed for period t. $E_t[\cdot]$ denotes the conditional expectation operator, based on the information available at time t. Similarly, $Cov_t(R, \cdot)$ denotes the conditional covariance between asset returns and market portfolio (or the state variables). λ_t and $\boldsymbol{\gamma_t}$ denote the price of market and intertemporal risk, respectively.

There are different approaches in the empirical asset pricing literature to estimate this model. We take a fully parametric approach, where quantities of interest in Equation (1) are recovered through several steps. The next subsection discusses how we estimate the conditional second moments and the prices of risk.

2.2 Empirical specification for the price of risk

We first separately estimate time-varying covariances for each asset, implementing the Asymmetric Dynamic Conditional Correlation (ADCC) specification proposed by Cappiello, Engle, and Sheppard (2006).[4] This allows us to accommodate different comovement in recession and expansions (Longin and Solnik, 2001). Then we specify an asset pricing model and estimate the common prices of risk through linear panel regressions, using the fitted conditional covariances as regressors. For this step, we extend Bali and Engle's 2010 methodology, who estimate a constant price of risk, by further conditioning the price coefficients of the model on a set of information variables through interactions. More formally, our empirical specification of Equation (1) is:

$$r_{i,t} - r_{f,t-1} = \alpha_{t-1} + \lambda_{t-1}\text{Cov}_{t-1}(r_{i,t}, r_{m,t}) + \sum_{j=1}^{L} \gamma_{t-1,j}\text{Cov}_{t-1}(r_{i,t}, z_{j,t}) + \epsilon_{i,t} \tag{2}$$

where, $\alpha_{t-1} = \boldsymbol{\alpha}' IV_{t-1}, \lambda_{t-1} = \boldsymbol{\lambda}' IV_{t-1}$, and $\gamma_{t-1,j} = \boldsymbol{\gamma}_{\mathbf{j}}' IV_{t-1}$. $\mathrm{IV_t}$ is a set of K demeaned information variables, available to investors at time t and includes a constant. The bold symbols are vectors of coefficients for each information variable. Consistent with ICAPM theory, we construct the panel such that all test assets face equal prices of risk, i.e. λ_t and $\gamma_{t,j}$. Excluding the information variables from the vector $\mathrm{IV_t}$, this specification nests the constant price of risk model, as in

[4] Please refer to Appendix A for a detailed explanation of the ADCC methodology and a discussion of the estimation results.

Bali (2008), where the prices of risk are considered to be time-invariant (See Appendix B).

In this setting, the *conditional* prices of risk can be interpreted as the derivative of the excess returns with respect to their covariance with the respective state variable. Thus, it is straightforward to derive their conditional standard errors from (2). For example, for the price of market risk, λ_t, we have:

$$\text{Var}\left(\frac{\partial R_i}{\partial \text{Cov}\left(R_i, R_m\right)} \,\middle|\, IV\right) = \text{Var}\left(\lambda_0\right) + IV^2 \ \text{Var}\left(\lambda_1\right) + 2IV \ \text{Cov}\left(\lambda_0, \lambda_1\right) \tag{3}$$

Here, λ_0 is the first element of the vector $\boldsymbol{\lambda}$ and represents the coefficient for the constant in the IV_t while λ_1 is the second element that represents the coefficient for the information variable in the IV_t.[5] The conditional intercept, α_t, and the conditional price of the intertemporal risk factors, $\gamma_{t,j}$, are similarly estimated. Based on these conditional estimates, we then calculate confidence intervals at each time period and for each price of risk. These allow us to study changes in the conditional prices of risk both in the time domain (i.e., a specific period) and in the information variable domain (i.e., a specific range of the variable's distribution values).

2.3 Risk Factor Contribution

Once the time-varying measures of risk $\widehat{\text{Cov}_t}(.,.)$, and the price of risk, e.g., $\widehat{\lambda}_t$, are estimated for each factor, we calculate the required reward from that factor based on the product of these values. Then we compute the magnitude of that reward in comparison to that of the other factors, for each asset at each point in time. We interpret this metric as the relative contribution of each factor to the asset's risk premia. For instance, for the market risk:

$$\text{Market}_{i,t}^{FC} = \frac{\left|\widehat{\lambda}_t \widehat{\text{Cov}_t}\left(R_{i,t+1}, R_{m,t+1}\right)\right|}{\left|\widehat{\lambda}_t \widehat{\text{Cov}_t}\left(R_{i,t+1}, R_{m,t+1}\right)\right| + \sum_j \left|\widehat{\gamma_{t,j}} \widehat{\text{Cov}_t}\left(R_{i,t+1}, z_{j,t+1}\right)\right|} \tag{4}$$

By taking the absolute values, we consider the same weight for the positive and negative effects of each risk factor. The contribution of a factor over a certain subperiod τ and subset of assets G

[5] For ease of exposition we present the case of only one information variable in the IV_t set. Appendix C provides the conditional variances of the estimates in the case of K information variables.

is then defined by the mean of these values in that subsample:

$$\text{Market}^{FC}_{G,\tau} = \frac{1}{||G|| \times ||\tau||} \sum_{i \in G} \sum_{t \in \tau} \text{Market}^{FC}_{i,t} \tag{5}$$

Where the operator $||.||$ denotes the size of the subsample. Therefore, higher values for $\text{Market}^{FC}_{G,\tau}$ indicate that market risk represents a larger share of the risk premia over subperiod τ and for subset G.

2.4 Feature Attribution and SHAP Values

In the last step, we explore through the business cycle and across industries the drivers of the assets' estimated risk premia. To this aim, we exploit the information content of a rich set of industry characteristics, which are commonly used in the asset pricing literature to investigate how these characteristics contribute to the cross-section of expected stock returns.[6] Due to issues of dimensionality, multicollinearity, and nonlinearity, ordinary least square techniques are not suitable for inferring their association with expected returns. Therefore, we benefit from the recent developments in the field of high-dimensional machine learning methods to overcome the empirical challenge. Appendix D introduces these methods and Section 5.2 discusses our selection procedure.

Although these advanced machine learning techniques tend to outperform linear ones in fitting the data, they offer little intuition of the underlying structural relationship between the explanatory and dependent variables. More specifically, it is not clear which drivers are predominant and, importantly, at which periods certain features contribute to the model outcome more strongly. To address these questions, we exploit SHAP values for each explanatory variable, constructed from the fitted values of the machine learning model.[7,8]

[6] A growing literature uses firm characteristics with machine learning algorithms to forecast stock returns (see, for instance, Rapach, Strauss, Tu, and Zhou, 2019; Freyberger, Neuhierl, and Weber, 2020; Gu et al., 2020; Kozak, Nagel, and Santosh, 2020; Leippold, Wang, and Zhou, 2022; Bryzgalova, Pelger, and Zhu, 2023). Differently from this literature, we focus on model-implied expected returns to study which firm characteristics shape prices of risk through the business cycle.

[7] Analyzing firm-level returns, Demirbaga and Xu (2023) also use SHAP values to explain the reasoning behind return predictions made by various complex machine learning models.

[8] An alternative approach to enhance the explainability of machine learning models is the Local Interpretable Model-agnostic Explanations (LIME) technique (Ribeiro, Singh, and Guestrin, 2016), which provides a linear approximation of the model for each predicted value. The advantage of the SHAP technique over LIME is that it offers a global explanation based on the entire dataset, not just one observation. Thus it results in importance metrics that are consistent across all model outcomes.

SHAP stands for SHapley Additive exPlanations and is a unified framework for explaining the output of machine learning models (Lundberg and Lee, 2017). In simple terms, SHAP quantifies the marginal contribution of each feature to the prediction made for each observation. The core concept is rooted in the Shapley value from cooperative game theory, which quantifies the marginal contribution of each player to the game, based on the outcomes of all possible combinations of players. In the following, we explain this concept in our context and in the same spirit of R-squared calculations, which we assume is more familiar to finance researchers.

The spread between the fitted values of a specific model that encompasses all features and the average value of the dependent variable represents the aggregate contribution of all features compared to a naïve estimator that only predicts the mean of the sample. SHAP extends this idea to each feature $k = 1, ..., K$. The procedure to calculate the Exact SHAP values involves constructing a set of all possible combinations of features.[9] That is, we draw $n = 1, \ldots, K$ features from the whole set of explanatory variables, and label the subset X^l ($l = 1, \ldots, L$ and $L = 2^K$). Then we train our choice of machine learning technique using this set of features on the whole sample of observations. Let $f_{\{\Theta^l\}}\left(X_m^l\right)$ denote the fitted value for observation m (industry i - week t) from the subset l which has n features. Θ^l is the set of learnable parameters for the model. We repeat this procedure for all possible combinations of n features.

Suppose X^l is a coalition set of explanatory variables with $n-1$ features except for feature k, and let $X^{l \,\cup\, k}$ be the set of the same explanatory variables which also includes feature k. The marginal contribution of feature k for the fitted values at observation m with respect to these sets is:

$$MC_{l;k;n}(m) = f_{\{\Theta^{\mathrm{l} \,\cup\, \mathrm{k}}\}}\left(X_m^{\mathrm{l} \,\cup\, \mathrm{k}}\right) - f_{\{\Theta^{\mathrm{l}}\}}\left(X_m^l\right) \tag{6}$$

Note that for $n = 1$, $X^{l \,\cup\, k}$ only includes feature k and X^l is an empty vector with no features, and thus $f_{\{\Theta^l\}}\left(X_m^l\right)$ is an estimator which simply predicts the mean values of the dependent variable. For $n = 2$, $X^{l \,\cup\, k}$ could be $K-1$ different sets that include feature k in addition to one more feature and X^l only includes that other feature. Similarly, for $n = K$, $X^{l \,\cup\, k}$ includes all K features (i.e., it is X) and X^l includes all but feature k. SHAP values for feature k are calculated by aggregating

[9] Lundberg and Lee (2017) consider path dependencies in a decision tree, which reduces the computational complexity. Furthermore, their Python library employs approximations and stochastic samplings to further decrease the need to train models based on all the possible combinations of features.

these marginal contributions across all coalition sets:

$$SHAP_k(m) = \sum_{l=1}^{L} w_{j;l;n} \times MC_{l;k;n}(m) \tag{7}$$

Where $w_{j;l;n}$ is the weight for the marginal contribution of feature k in set $l \cup k$, which includes n features. There are several restrictions on these weights. First, they sum up to one. Furthermore, due to symmetry, the weights of the marginal contributions for all n-feature models are equal. Lastly, to impose a fair attribution at each concession across these additive coalition sets, the sum of the weights of marginal contributions for n-feature models is equal to the sum of the weights for p-feature-models (for any $p = 1, \ldots, K$). The weight of a marginal contribution for a n-feature model is the reciprocal of the number of possible marginal contributions to all the n-feature models. These conditions result in a unique solution for these weights.

Once the SHAP values of each feature are calculated for each observation, we take their mean absolute values over asset subset G and subperiod τ to measure the importance of each feature, similar to Equation (5).

$$\text{SHAP}_{k,G,\tau} = \frac{1}{||G|| \times ||\tau||} \sum_{m \in G \cap \tau} |SHAP_k(m)| \tag{8}$$

Due to their additive nature, the SHAP values of all the input features will always sum up to the difference between the current model's predicted output and the mean of the sample, a naïve baseline estimator's output. That is, we have $\sum_{k=1}^{K} SHAP_k(m) = E[y] - f_\Theta(X_m)$. Note that the SHAP value of feature k for observation m can be positive (negative) if this feature increases (decreases) the predicted outcome of the model for that observation. Thus its importance is gauged by the magnitude of its contribution to $f_\Theta(X_m)$, not its sign. Like a higher R-squared, a higher SHAP value suggests that the feature has a better association with the model outcome and thus we interpret that feature as a more important determinant of the estimated risk premia. Ultimately, we rely on SHAP values to discriminate and rank across all possible features.

3 Data

This section illustrates the data used in the empirical analysis. We study weekly US industry returns from the start of January 1986 to the end of December 2022, in an ICAPM framework which is augmented with macroeconomic risk factors and conditional on a set of commonly used information variables.

Filtering out stock properties linked to daily market-microstructure effects, the weekly frequency is particularly suited to our study, given the goal of capturing the impact of the economic and financial cycles. Since there is no generally recognized method to mark their evolving phases, in some of our tests we use NBER dating as a proxy method to identify the stages of the cycles. Over the 1930-week sample, the NBER recessions cover 157 weeks or 8.13 percent. Furthermore, the average duration of a recession is 39 weeks, thus a lower frequency, say monthly or quarterly, would decrease statistical power. The choice of the starting date is due to the availability of the conditioning variables with weekly frequency.[10]

3.1 Test assets

Inspired by Lewellen et al. (2010) and Daniel and Titman (2012), who argue that the usual test assets in cross-sectional studies (e.g., 25 size/Book-to-Market portfolios) have strong factor structure, we study industry portfolios. Furthermore, we take their recommendation and use the largest cross-section available for these portfolios. More specifically, we study the 49 industry portfolios based on firms' four-digit SIC code, downloaded as daily data from Kenneth French's online data library and compounded linearly to obtain weekly returns. Summary statistics of these samples are provided in Table 1.

[Place Table 1 about here]

In our classification of industries, we start from Morningstar Stock Sector description that distinguishes Cyclical Super Sectors (highly sensitive to business cycle peaks and troughs), Defensive

[10]Relaxing this constraint, we extend our analysis using the data from January 2^{nd}, 1962. Due to missing observations in the early period, and because our estimation approach requires a balanced panel, this results in five fewer industry portfolios and two fewer information variables. Our overall conclusion is not altered by this choice. The detailed results are available upon request from the authors.

Super Sectors (with anti-cyclical industries), and Sensitive Super Sectors (industries with moderate correlations with the business cycle). We attribute most of the disaggregated industries to one of these Super Sectors, validating our analysis with research from the Bureau of Labor Statistics that quantifies the sensitivity of industries' demand and employment to business cycle movements. The remaining industries (personal services, business services, and wholesale) are classified as "Others" as they include companies linked to both defensive and cyclical activities (see Table A1 for our classification of each industry).

3.2 State variables

There is no definite empirical measure established as state variable linked to the shifts in the future investment opportunity set. We thus investigate potential candidate risk proxies through long-term bond returns and innovations in macroeconomic variables. The choice of a long-term bond portfolio is supported by both theoretical and empirical papers in the literature (e.g., Merton, 1973; Chen, Roll, and Ross, 1986; Scruggs and Glabadanidis, 2003; Gerard and Wu, 2006). We use returns on US Treasury Bonds with 10-year maturities (labeled as Bond), which we collect from CRSP at the daily frequency and linearly compound to the weekly frequency. Innovations to macroeconomic variables are also commonly used in empirical asset pricing to proxy for intertemporal risk as drivers of hedging demands, since these variables directly impact the cost of capital, cash-flows and investment opportunities of firms (see for instance, Campbell and Vuolteenaho, 2004; Hahn and Lee, 2006; Petkova, 2006; Bali and Engle, 2010). Accordingly, we test the following set of macroeconomic variables, which we obtain from the Federal Reserve Bank of St. Louis data library: innovations in Term Spread (the difference between yields on 10-year Treasury bond and 1-year Treasury bill, labeled as ΔTS), innovations in Default Premium (the difference between yields on Moody's BAA-rated and AAA-rated corporate bonds, labeled as ΔDP), and innovations in the Effective Federal Fund rate (labeled as ΔEFFR).[11] Since these variables are highly persistent, their changes are close to estimated surprises. Summary statistics of the risk factors are provided in Table 1.

Unconditionally, the long-term bond or the macroeconomic variables we study do not robustly predict the market portfolio returns (Maio and Santa-Clara, 2012). However, period-by-period

[11] Merton (1973) initially suggests bonds and interest rates as potential state variables but lists other potential candidates for the intertemporal risk factor, such as shifts in the wage-rental ratio, and inflation. However, there is no reliable data for these variables with weekly frequency.

analysis suggests that such a relationship exists in the data, at least in certain episodes. Figure 1 visualizes these results, where we plot the slope coefficients for the state variables from moving_window predictive regressions of three-years-ahead market portfolio returns.[12] In the context of ICAPM models, as a result of investors' hedging demands, if a state variable forecasts positive future market returns, its innovation should earn a positive risk price in the cross-section. The plots indicate that the sign of the relationship between the state variables and future market portfolio returns changes over our time sample, which we will take into consideration for the interpretation of our unconditional tests. At the same time, we do observe sub-periods of statistically significant predictability for the Bond returns and for the innovations in Term Spread and in Default Premium.

For the market portfolio, we use the value-weighted NYSE/ AMEX/ NASDAQ index from CRSP. For the risk-free rate, we use the one-month T-bill rate, sampled at the weekly frequency, obtained from Kenneth French's online data library.

[Place Figure 1 about here]

3.3 Conditioning (Information) Variables

For conditioning information for the prices of risk, we use the information from two types of variables that we lag and demean in estimation. These have the support of the predictability literature (see among others: Fama and Schwert, 1977; Keim and Stambaugh, 1986; Campbell and Shiller, 1988; Fama and French, 1989). We use macroeconomic-related variables such as Default Premium (DP), Term Spread (TS), and short-term interest rates (T-bill). We also use financial market variables, such as the excess US market dividend yield (DY), the TED spread (TED), and the VIXO Index (VIXO). We obtain them from the Federal Reserve Bank of St. Louis data library at the daily frequency and use their values on Fridays (or the last values per week in case of a statuary holiday) to convert them to the weekly frequency.[13]

[12] The choice of three years is motivated by the evidence in Maio and Santa-Clara (2012). However, our conclusions also hold for other horizons such as 1, 2, 5, 7, and 10 years ahead. The results are available from authors upon request.

[13] DY is calculated from the difference between the previous year's annualized market returns including distributions and the one excluding distributions, divided by the value of the index excluding distributions.

3.4 Firm Characteristics

We collect 69 industry characteristics from the WRDS Industry Financial Ratio (WIFR) dataset which are aggregated from firm-level financial variables. At each period, we choose to study median firm values in each industry to limit the effect of outliers. We also calculate four industry return characteristics from their daily returns. They are all grouped into nine categories, following WIFR grouping: (1) Return, which measures the financial performance of firms' stocks, (2) Valuation, which estimates the attractiveness of a firm's stock, (3) Profitability, which measures the ability of a firm to generate profit, (4) Efficiency, which captures the effectiveness of firm's usage of assets and liability, (5) Financial Soundness, which measures the operation health of the company, (6) Capitalization, which measures the debt component of a firm's total capital structure, (7) Solvency, which captures the firm's ability to meet its long-term obligations, (8) Liquidity, measures a firm's ability to meet its short-term obligations, and (9) Other, which are miscellaneous ratios and do not fall in the above groups. Previous research analyzing equity returns finds predictive ability for many of these characteristics (for example, Soliman, 2008; Ball et al., 2016; Medhat and Schmeling, 2022). In the analysis of Section 5.2, we take the one-period lag values of the industry characteristics. See Tables A2 and A3 for more description.

4 The Prices of Risk Through Time

We start our analysis with a trailing window estimation of the constant price of risk model. Figure A1 plots the year-by-year price of market risk obtained from a specification of the ICAPM which assumes that $\gamma_j = 0, \ \forall \ j$.[14] The NBER recession periods are marked by gray bars on the plot. The choice of a one-year window is motivated by the average duration of the recessions in our sample (39 weeks per recession), thus we believe we can broadly capture differences in economic conditions within our estimation window. Visual inspection of the yearly estimated prices confirms previously reported evidence that (a) the price of risk is time-varying, and (b) the price of market risk increases during the recession periods. To better understand what drives these temporal patterns, we turn to the ICAPM specifications where the time variation in the compensation for risk

[14] Appendix B table A5 presents the results of the constant price of risk models for the ICAPM under different specifications. For the price of market risk it documents comparable estimates to those reported in previous research. The plotted coefficient is the one of specification (1) that only includes market risk.

is related to conditioning variables linked to fluctuations in the economic and financial cycles.[15]

4.1 Conditional Price of Risk

The NBER recession and expansion periods are identified ex-post based on various economic indicators, which are not available to investors ex-ante. Therefore, they are not informative for decision-makers in the stock market. Instead, we analyze the price of risk, directly conditional on the lagged values of economic and financial variables, estimating Equation (2) with one IV_t at a time. Table 2 presents the results. Given that our information variables are demeaned, in this table, the constant (*Level*) coefficient represents the marginal effect for the conditional risk when the $IV_t = 0$, i.e., when the economy is most likely not at a peak or a trough of the cycle. In other words, it is pointing to risk that matters in normal economic conditions. The plots of the values for the information variables in Figure A2 over the time sample, with the NBER recession periods marked by a gray bar, are a reminder that the "normal" corresponds to the mid-cycle. The slope (*Interaction*) coefficient instead captures the variation in the price of a risk factor through highs and lows in the cycle.

In Panel A of table 2 we observe that the *Level* coefficient for the price of market risk is positive and highly significant across all six conditioning variables. The evidence is quite robust, with the magnitude in line with what we find in Table A5. The *Interaction* coefficient on the DY is positive and significant, suggesting that the price of market risk is increasing in the aggregate dividend yield. A higher dividend yield is mostly present in recessions when stock prices are relatively low and dividend payouts are less volatile.

The evidence on the significance and variation of the potential proxies for intertemporal risk is an improvement on the results of the constant price models of Table A5. The sign of the level coefficients is consistent with the one estimated in the latter table. Additionally, in table 2 we find statistical significance for the long-term Bond (Panel B) and for the innovation in the Default Premium (Panel D). Except in two cases, the *level* coefficient for these risk proxies is either strongly or marginally significant, thus we find support for the importance of at least one additional risk factor, even under normal economic conditions. The evidence on time-variation for intertemporal

[15] The moving window approach is sensitive to the choice of the estimation window and suffers from low power, besides the shortcomings in characterizing the dynamics in real-time.

risk is even stronger than for market risk in two of the proposed proxies and similar to the market for another one. A few conditioning variables (TS, TED, and VIXO) are positive and significantly related to the Default Premium risk while the DY is negative and highly significant, for both the Default Premium and long-term Bond risk factors. For the Term Spread risk, time variation is highly supported through the conditional relationship with the DY, T-Bill, DP, and VIXO variables. Overall across all types of risks, the DY is a statistically strong conditioning variable, reflecting its previously documented importance as a reliable stock market predictor. In our tests, we show that its power extends also to other sources of risk. The only state risk proxy with no statistical support is the innovations in the Effective Federal Fund Rate. It is plausible that this insignificant result is related to the unique monetary regime in the period we study. Almost half of our sample time corresponds to the period of near-zero interest rates from the 2008 financial crisis to the COVID-19 crisis and there is possibly little information to capture in the estimation.

[Place Table 2 about here]

To go beyond what can be learned through the tables of coefficients, we turn to an illustration of the risk-return tradeoff. Figure 2, panel (a) and (b) for the price of the market and of one intertemporal proxy, and Figures A3 - A5 for the remaining ones, depict the marginal effect of risk on expected returns, conditional on the information variables. In each plot, the y-axis shows the estimated price of risk based on the distribution of the conditional variable on the x-axis. The plots also report the 95 percent conditional confidence intervals to help in assessing the values for which the association is statistically significant. We can thus shed light on the changes in the price of risk through values of a single conditional variable that corresponds to different economic and financial conditions.

The plots in Figure 2a illustrate the variation of the price of market risk from the estimates tabulated in Panel A, Table 2, and show this price as positive and significant for normal economic conditions. Moreover, the conditioning intervals for the coefficients never encompass zero over the range of the conditional variables. A very interesting pattern is illustrated for the price of intertemporal risk in Figure 2b and in Figure A3 through A5, obtained from the coefficients in Panel B through E of Table 2. Across these plots, we mostly find significance over the more extreme conditioning values, which likely coincide to the troughs of recessions, the peaks of expansions, and periods of financial stress. These are meaningful values because they relate to very important points of the economic and financial cycle, while we find that the constant, which corresponds to average/neutral conditions, is often not significant.

More specifically, the intertemporal risk, as proxied by the long-term Bond returns and the changes in Default Premium, is significant when the DY is below its historical average value. However, as the DY increases, as it happens during the recession periods, the economic as well as statistical importance for the risk factors decreases. The opposite trend is observed for the Term Spread risk, where the DY only matters to the extent that it modifies the relationship above its average, thus for values that are observed increasingly in bad times. Similarly, from the plots for the Default Premium risk in Figure 2b conditional on TS, and for the Term Spread risk in Figure A4 conditional on DP, we observe that the compensation for intertemporal risk is low in expansion and increasing in values of the conditioning variables above their average which are highly associated with recessions. Analyzing the results for the financial variables, we find that the Term Spread and Default Premium risk factors are significant and are associated with an increasing price when conditional on large values of the VIX index, which occur during financial markets turmoil. Default Premium risk is also significant conditional on large values of the TED spread, which are recorded at times of funding problems, thus also in this case, an indication of economic and financial stress. Finally, the conditioning information from the T-Bill is only significant as a driver of the Term Spread risk. We observe that its price is becoming more negative in good times for above-the-average values of the short-term interest rate that are mostly associated with expansions. Putting together this evidence with the previous discussion on Figure A4, we can infer that the compensation for intertemporal risk as proxied by the changes in Term Spread is not required in normal states of the economy. As for the evidence of Panel E Table 2, Figure A5 shows that the innovations in the Effective Federal Fund Rate used with a single conditioning variable is not an effective proxy for intertemporal risk.

Across the plots, we also mark with a dotted line the magnitude of the conditional price to help the reader assess the difference between the estimated prices in good and bad times. In the vast majority of cases, the difference is statistically significant. We conclude that the systematic variation between the extreme values of the conditioning variables overall provides power to reject the null hypothesis for the significance of the risk factors, which we are not able to achieve in the constant price model of Table A5. This kind of pattern can be an explanation as to why it has been challenging to uncover intertemporal risk with the help of different proposed proxies while relying on tests of unconditional asset pricing models.

[Place Figure 2 about here]

4.2 Time-varying Price of Risk

Motivated by the evidence in Section 4.1, we proceed to estimate the time-varying prices of risk, pooling all information variables in the same regression, rather than one IV_t at a time. We present the summary of the test results in Table 3 and refer readers to Appendix Table A6 for the individual estimated slope coefficients and their associated standard errors.

In Table 3 the results for all risk prices are organized in the same order. For example, the first Wald test, $H_0 : \lambda_t = const.$, is for the joint significance of the coefficients for the price of market risk, excluding the intercept. Given that our information variables are demeaned in these estimations, this hypothesis tests for the time-variation of the price of market risk, when the information variables are away from the zero value, thus for highs and lows of the economy. The second test, $H_0 : \lambda_t = 0$, is for the joint significance of all the coefficients of the price specification including the constant, and thus it establishes evidence that the price of market risk is significant in all states of the economic cycle. Lastly, through the third test, $H_0 : \overline{\lambda_t} = \widehat{\lambda}$, we check if the mean of the time-varying prices of risk is equal to the estimate from the constant price model, tabulated in Table A5, column (1) through (5) respectively. This further sheds light on the dynamic patterns of these prices of risk.

The reported p-values for the joint Wald tests are suggestive of priced risk factors since they all strongly reject the null. The risk-return relationship is significant at any significance level not only for market covariance risk but also for the additional intertemporal risk proxies. With these unconditional tests of a conditional relationship, we find evidence of time variation through the full dynamics of the cycles when combining the information from the multiple variables. We also find that the mean of the estimated time-varying prices of Term Spread, Default Premium, and Effective Federal Fund Rate risk are significantly different from their constant price of risk estimates, which again highlights the challenges in uncovering intertemporal risk with tests unconditional models. On the other hand, we fail to reject the third null hypothesis for the λ_t, an indication that accounting for time-varying conditional information is not crucial to finding support for market risk.

[**Place Table 3 about here**]

We provide more insights on the time-variation of these prices through changing economic conditions in Table 4 Panel A. All the prices of risk have a positive average value over the entire time sample with the exception of the one for the changes in Term Spread, which is the only proxy with positive unconditional correlation and conditional covariances in expansion periods (see respectively Table 1 and A1). We also provide a two-tailed test of equality between the expansion and recession means. While the evidence on the statistical difference for the market price is not robust across the different model specifications, it is very strong for the intertemporal risk, regardless of the proxy and the specifications. The results of these equality tests are consistent with the insights provided by Figure 2 and A3 - A5 on the importance of differentiating between highs and lows of the cycle to empirically capture changes in future investment opportunities. In Panel B, we present the slope coefficient for the trend in these time-varying prices during the NBER recession periods.[16] We observe that the price for the market, Term Spread, and EFFR risk factors are increasing during recessions, while we document a downward trend for the price of the Bond and Default Premium risk factors. Only in the specification with changes in the Default premium, the market has a small negative trend.[17]

[**Place Table 4 about here**]

To visually evaluate these patterns, we turn to the plots of the time-varying prices of risk with their conditional confidence intervals in Figure 3, where we provide precise inference on the dynamic behavior of the prices of risk in the common time domain. Here we combine the estimation uncertainty of the regression coefficients with the variability of the information variable at each

[16] More specifically, we estimate regressions of time trend interacted with an NBER recession dummy. For example, for the price of market risk, we run the following regression and report the slope coefficient b_1 multiplied by 52:

$$\lambda_t = b_0 \; + \; b_1 \, t \times \mathbb{1}_{Rec.} \; + \; r_j \; + \; u_t,$$

where $\mathbb{1}_{Rec.}$ is a dummy variable that takes the value of one if week t falls in the NBER recession periods, r_j are individual NBER recession fixed effects, and u_t is the error term.

[17] Once we take care of high-frequency dynamics with an HP filter, all the estimated trend coefficients for the market are positive.

period, expanding the computation from Equation (2) to additional conditioning variables. The information that we gather from this analysis thus complements the insights from Figure 2a (and A3 - A5) where instead we plot the estimated prices over the range of values in the information variables. Conditioning on multiple time-varying variables enhances the counter-cyclical dynamics for the market risk as shown in Figure 3, top plot. As the economy moves through a recession, which is marked by a gray bar, the required risk compensation is increasing, and it remains statistically significant in most of those recession weeks. In Figure 3 bottom plots, we observe that the prices for the proxy risk factors have both positive and negative values. Except for the Term Spread risk, the prices are positive and significant in the majority of the expansion weeks, while not significant when negative. Coupled with the negative covariation between the assets and the state proxies that we observe in Appendix Table A4, this finding points to a negative component in total risk premia. It is also consistent with the notion that during expansions, those industries with larger negative covariation are better positioned to help investors offset uncertainty linked to the future path of the economy. Many assets' covariations with the changes in Term Spread are instead positive, while its price is at times negative, also implying a negative component in the total risk premia. Taking the evidence across the candidate state proxies together, our finding on the sign of the intertemporal risk premia suggests that through these postulated factors we are able to capture a hedging component that is distinct from the required reward for market risk. Furthermore the evidence strongly indicates that the variation through the highs and lows in the economic and financial cycle provided by the conditioning information is a key aspect in capturing such components.

[**Place Figure 3 about here**]

5 Determinants of Risk Premia

To better understand risk dynamics through the economic and financial cycles and across industries, we explore in this section the drivers of the risk premia, implied from the prices estimated in Section 4. Scrutinizing the implied risk premia and analyzing the cross-section of test assets with varying sensitivity to the cycles allow us to evaluate the importance of the intertemporal risk for investors. To this aim, first, we study the factor contribution for each source of risk, as defined in Equation (5). This helps us gauge the relative importance of each risk factor in explaining the risk premia. Next, we dig further through firm characteristics and explore the determinants of the risk premia using SHAP values, as defined in Equation (7). We use the risk premia estimated from the prices of risk in Specification (6), which pools all the macroeconomic risk factors.[18]

5.1 Risk Factor Contribution

Table 5 reports the contribution of each risk factor to the portfolios' risk premia through the business cycle and over the industry groupings. In Panel A, we find that the market risk explains about 55% of the total risk premia throughout the sample.[19] The intertemporal share is thus substantial, accounting for almost half of the risk premia, with the changes in Default Premium the most relevant of the three factors. When focusing on differences across recessions and expansions, the magnitudes are very close. However, in statistical terms, they matter. The test of means rejects the null of equality across the periods for all risk factors, documenting a non-linear relationship between risk and reward through the business cycle. For the market and two of the intertemporal risks, the trend dynamics corresponding to the NBER recessions are statistically significant. Market risk premia are increasing in downturns, consistent with countercyclical patterns in the aggregate and also highlighted in Panel B, Table 4. Intertemporal risk is instead decreasing, suggesting that the offered discount from holding at least some assets seen as safe is not quite as important in bad times.

Evaluating the relative importance of each risk factor for industry groupings delivers additional insights. In Panel B, the share of market risk is larger for Cyclical industries while the one for intertemporal risk is larger for Defensive industries, and this difference is statistically significant for two of the three proxies. This aligns with the view that firms in the Defensive sectors are better positioned to help investors capture changes in investment opportunities. Putting this evidence together with the one from Panel A helps explain why for example firms in Defensive industries, such as Food or Healthcare tend to outperform their counterparts during the recession periods (see Table 1).

[18] The results for the other specifications are qualitatively comparable and are available upon request.

[19] Note that by construction, the sign of the factor risk premia is masked in this statistic. As a result, in the presence of negative prices or of measures of risk, this statistic can be larger than 1 for the rest of the risk factors.

[Place Table 5 about here]

5.2 Industry Characteristics and Risk Premia

Table 5 documents significant variations in sensitivity to risk factors in the cross-section of assets and through time. The extent of these diverse risk exposures is likely influenced by disparities in industry-specific characteristics. Thus, in this section, we exploit the information content of a large set of characteristics that are closely monitored by investors as informative signals of firms' economic and financial conditions in different states of the economy. Some of these have been studied in the asset pricing literature to identify the important drivers of the risk premia and have been shown to be informative about firms' fundamental values and changes in their stock prices. For example, Chen and Zhang (2007) show that variables such as earnings yield, capital investment, and changes in profitability and growth opportunities, have predictive power for future stock returns. Medhat and Schmeling (2022) document that double sorting on the previous month's return and share turnover reveals short-term reversal among low-turnover stocks. Papers such as Campbell and Shiller (2001) report that price-earnings and dividend-price ratios appear to be useful in forecasting future stock price changes. Ball et al. (2016) document that expected returns increase in cash-based operating profitability, which even subsumes accruals in predicting the cross-section of average returns. Soliman's (2008) results suggest that investors react to changes in asset turnover. Bhandari (1988) finds that the expected common stock returns are positively related to the ratio of debt to equity.

Due to dimensionality, multicollinearity, and nonlinearity among the 73 characteristics, we exploit recent developments in the field of high-dimensional machine learning methods to select the best-performing technique in predicting the cross-section of industry risk premia. In the next step, exploiting the SHAP values implied by the adopted technique, we can identify the attribution of each industry characteristic to the compensation of risk through the cycle and across sectors.

Building on Gu et al. (2020), Bali, Beckmeyer, Mörke, and Weigert (2023), and Leippold et al. (2022), we stay agnostic on the choice of the structural relationship between the dependent variable (i.e., the asset estimated risk premia, labeled y) and the explanatory variables (i.e., the asset characteristics, labeled X). Instead, we select the one with the highest predictive performance in our sample. We apply several widely-used machine learning techniques, including linear regressions with dimension reduction (least absolute shrinkage and selection operator, Ridge, Elastic Net, principal component analysis, and partial least squares regressions), decision trees (random forest regressions, gradient boosted regression trees, and extreme gradient boosting (XGBoost) methods), and neural networks (feed-forward neural network called Multi-layer Perceptron).[20,21] These are carefully picked with the purpose of reducing the dimensionality concerns in our feature set, which includes several highly correlated variables.[22] In addition, some of these models allow us to incorporate a nonlinear relationship between the industry characteristics and risk premia, which might be observed as a result of cyclicality.

Table 6 tabulates the results of the horserace among these techniques. First, we observe that the in-sample and out-of-sample R-squared metrics for most models are comparable, suggesting that the regularization terms in our implementations successfully prevent overfitting in these estimations. From the results in Table 6 we find that linear models tend to perform poorly both in-sample and out-of-sample. Their out-of-sample R-squared ranges from 0.113 to 0.136. The underperformance of the linear models is consistent with the findings in Table 3 where we show that the price of risk changes significantly, perhaps nonlinearly, through the cycles. The neural network operator performs much better than the linear models but not as well as the decision tree ones. This is not surprising because, by design, neural network operators with multiple layers involve estimating a significantly larger number of model parameters. Therefore, these models tend to perform better when fitting a much larger training set. On the other hand, with short to medium time series, as our sample, previous research finds support for decision trees (see, for example, Gu et al., 2020 studying stock-level and Akbari et al., 2021 studying country portfolios). Table 6 confirms these findings in our data, where we find that the XGBoost model performs the best. This technique generated the largest coefficient of determination, with an in-sample R-squared of 0.761 and a predictive R-squared of 0.539. It also results in the lowest forecast errors, as measured by the mean

[20]Recently, Feng, Giglio, and Xiu (2020) and Freyberger et al. (2020), using a modified LASSO operator, and Kozak et al. (2020), using a Bayesian principal components estimator, identify the relevant risk determinants for the cross-section of stock returns in a high-dimensional setting. Bali et al. (2023) argue that one can improve the prediction quality of these techniques by combining the predicted values of several models. The latter approach, unfortunately, reduces the explainability of the estimations.

[21]Please refer to Appendix D for a detailed description of our implementation and choices of hyperparameters for each of these models.

[22]See Figure A6 for a heatmap diagram of their cross-correlation in our sample.

absolute prediction error and the root mean squared prediction error metrics.

[Place Table 6 about here]

For the previous exercise, we focus on estimated expected returns, rather than realized returns that are contaminated by noise. This requires that we take a stand on a parametric model. When we compare the results of a similar experiment performed on realized industry returns, we find much smaller in-sample R-squared for all models and much weaker performance out-of-sample.[23] That said, we also observe that the XGBoost model outperforms the other machine learning models in predicting realized returns with an in-sample R-squared of 0.203. See Table A7.

Having identified the best model in explaining the risk premia, we calculate the SHAP values to attribute the prediction outcome to the different features. The higher the SHAP values of a feature, the more important that feature is for predicting the dependent variable. As a descriptive example, in Figure 4 we plot the top 10 features (i.e., those with the largest SHAP values) for the Trading industry which includes brokers and investment services, on March 15, 2009 (an NBER recession date) and on March 17, 2019 (an NBER expansion date). The graphs show how much each feature increases (decreases) the predicted output of the model, noted as $f(x)$ on top of the graphs, from the naïve estimator that only relies on the mean of the sample, noted as $E[y]$ on the bottom of the graphs. In this example, Enterprise Value to EBITDA (*evm*), Market Value of Equity to Net Cash Flow from Operating (*pcf*), Interest as a fraction of average Total Debt (*int_totdebt*), and Payables Turnover (*pay_turn*) change the predicted outcome the most on that specific expansion date, whereas stock risk (*indstd_ret*), Shiller's Cyclically Adjusted P/E Ratio (*capei*), Enterprise Value to EBITDA (*evm*), and Sales per dollar of Invested Capital (*sale_invcap*) are the most influential characteristics in driving the predicted outcome in the recession date.

[Place Figure 4 about here]

Similar to Section 5.1, we aggregate the absolute SHAP values for the categories over the phases of the business cycle and over the cross-section of broad sector groupings. Table 7 presents these statistics, and we refer readers to Appendix Tables A8, A9, and A10 for a more granular

[23] See Rapach et al. (2019) for industry return prediction using lagged industry returns from across the entire economy, where authors also find that equity returns inherently contain a relatively small predictable component.

presentation of the results across phases of the cycle, industries and characteristics. In Panel A we report the sum of the SHAP values per characteristic category over time periods. Specifically, the first row presents the mean absolute SHAP values over all industries and the whole period, which suggests that throughout the time sample, the Valuation category is the most important driver of risk premia with average aggregate SHAP values of 36.212. The asset pricing literature, mainly using the portfolio sorting approach, also finds that the variables in this category have predictive power for the cross-section of equity returns (see, for instance, Fama and French, 1992 and Campbell and Shiller, 2001). In second and third place behind Valuation are the Financial Soundness and Efficiency categories, with SHAP values of 17.455 and 14.068, respectively. These characteristics have a measurable impact on a firm's ability to meet its obligations and the effectiveness of the firm's usage of assets. Solvency and capitalization are ranked at the bottom, at 3.631 and 1.764. So in all, the method provides a useful approach to meaningfully compare large amounts of information.

Analyzing SHAP values over expansion and over recession periods, in Panel A we observe that the contribution of these features changes; a two-tail test of means rejects the null that the averages of the SHAP values in each category are equal in the two subsamples, except for the Financial Soundness categories. The coefficient on a time trend regression shows that in recessions the importance of the Return category increases the most in magnitude. Among the features in this category in Appendix Table A8, the stock risk (*indstd_ret*) becomes the most important one, with an increases of 135.53% from expansion periods. Research on loss aversion and downside risk documents that investors care about losses differently from upside gains, and they have predictive power for future asset returns. For instance, papers such as, Ang et al. (2006a), document a downside risk premium in the cross-section of stock returns. More recently Bollerslev et al. (2022) show that betas stemming from negative market and negative asset return covariation significantly predict future returns. Panel A shows that the Valuation category is also increasing in importance during bad times. In Table A8 SHAP values for Shiller's Cyclically Adjusted P/E Ratio (*capei*) and Sales per dollar of Invested Capital (*sale_invcap*) grow by 140% (from 3.226 to 7.741) and 98% (from 2.104 to 4.171), respectively in the recession periods.

Analyzing the relative importance rank, rather than the magnitude of the SHAP values, a similar pattern is observed in Appendix Table A11: with the highest SHAP Values in all periods, *evm* and *pcf* are ranked as top two characteristics on average across all industries. This suggests that the above valuation metrics are informative signals for investors irrespective of the overall business conditions. They are indicative of firms' future cash flows, which depend on the scale of operations, with the level of capital investment affecting the scale of existing operations, and changes in growth opportunities affecting expected future scale (Chen and Zhang, 2007). However, in the NBER recession periods some features gain importance; noticeably, the rank for *sale_invcap*, *capei*, and *indstd_ret*, on average, improves by 7, 6.5, and 5.0, respectively, with them taking the spot of characteristics such as *int_debt* among the top ten.

[Place Table 7 about here]

Next, we explore the feature attribution to the industries' risk premia in Panel B, where we distinguish the aggregated absolute SHAP values like in Panel A but across sector classification. We observe a pattern across industry groups similar to Panel A, with Valuation and Financial Soundness as the most important categories overall. Panel B further shows that the attribution of these features differs across Defensive and Cyclical industries. In fact, we reject the null that the mean of SHAP values is equal for all feature categories within these industry groupings. Interestingly, the average SHAP values for the Sensitive industry group, which includes industries that we classified as neither Cyclical nor Defensive, are between those of the Cyclical and Defensive groups.

Differently from the Cyclical industries, for firms in the Defensive sectors, Return features are ranked third and more important than Efficiency features, with mean absolute SHAP values of 13.000 and 12.285 versus 9.547 and 11.351. The SHAP values for firms in the Cyclical and Defensive sectors vary the most across the Return and Valuation categories; with respect to Return, values are 3.452 point estimates larger for the Defensive sector while with respect to Valuation, they are 2.682 point estimates larger for the Cyclical one. In fact, the difference between any two sectors in any feature category SHAP values is smaller than the values above. Given that the Defensive industries are a hedge for investors during recessions, it is interesting to see in Appendix Tables A8, A9, and A10 that stock risk (*indstd_ret*), in addition to size (*indsize*) and payables turnover ratio (*pay_turn*) are the more important features for these firms, as compared to the Cyclical industries.[24] Conversely, among the valuation ratios, Enterprise Value to EBITDA (*evm*) and Market Value of

[24] Freyberger et al. (2020) using a modified LASSO methodology also find that Return category variables, such as size, volatility, and past returns, have incremental explanatory power for expected stock returns.

Equity to Net Cash Flow from Operating (*pcf*), in addition to Interest as a fraction of average Total Debt (*int_totdebt*) are the important ones for Cyclical firms which have larger profit swings through the business cycle.

It is worth noting that some characteristics are more important for some industries. For instance, *stdev_return* is ranked among the top three most important ones for firms in the mining sector, such as Petroleum and Natural Gas, Coal, Non-Metallic and Industrial Metal Mining, Precious Metals, Steel Works. However, it is not in the top ten for the Utilities, Wholesale, Food Products, Consumer Goods, or Healthcare firms. *pay_turn*, on the other hand, is consistently ranked among the top three most important characteristics for the majority of industries, except for the finance-related ones, and Banking, for which it is ranked 50. Similarly, *int_totdebt* is considered important for all but the Medical Equipment and Pharmaceutical Products firms, for which it is ranked 25.

In sum, our results suggest that a limited set of a large number of characteristics conveys the most relevant signals for the cross-section of industries and throughout the economic and financial cycles. The predictive nature of our results complements and expands research on the traditional sector rotation strategies based on macroeconomic variables (e.g., Rapach, Strauss, and Zhou, 2010, and Zhu, Yi, and Chen, 2020). Investors can rely on the proposed techniques to sort and narrow down independent information, which can be exploited for asset rebalancing strategies.

6 Conclusion

We investigate within the framework of an intertemporal asset pricing model the time-variation in the prices of risk in relation to the economic and financial cycles. Our specification accounts for sources of risk through state variables in a conditional setting, where the prices of risk factors vary with the information set of investors. We then analyze, with advanced machine-learning techniques, the determinants of these prices and of the resulting asset risk premia to provide investors with valuable insights for sector rotation strategies.

The evidence strongly indicates that information on the variation through the highs and lows of the cycles is a key aspect in capturing the statistical significance of the intertemporal components. Conversely, conditioning information is not crucial to finding support for market risk. In fact, while the price of market risk is positive and significant throughout, time-variation in intertemporal risk is statistically significant only at some stages of the cycles, mostly over troughs of recessions, peaks of expansions, and periods of financial stress. For example, the price of the default premium risk is significant during an economic downturn, when it decreases, and during tight funding conditions or high market uncertainty, when it increases.

Taking into consideration that most of the intertemporal risk proxies have negative covariances with the assets, the evidence overall suggests that the risk prices consistently generate a negative component in their risk premia. We show that the contribution of intertemporal risk is substantial, accounting overall for almost half of the total risk premia, with the innovations in Default Premium the most relevant. The share of market risk increases while that of intertemporal risk decreases during recessions. In the cross-section, market risk contributes more to the Cyclical industries' risk premia, whose sales are more heavily affected in bad times. Conversely, the intertemporal risk factors such as innovations in Term Spread or in Default Premium contribute relatively more to the risk premia of the firms in the Defensive sectors. The latter tend to outperform during the recession periods and provide a hedge to investors, which can explain why the intertemporal risk factors are relatively more important, yet smaller in recessions.

Further investigation through Machine Learning methods reveals that firm characteristics have a different association with the model-implied expected returns of the Cyclical and Defensive sectors. For instance, among the characteristics, the Valuation and Financial Soundness categories are relatively more important based on SHAP values for firms in the Cyclical industries, which have larger profit swings through the business cycle. The Return and Efficiency categories are instead more predominant for the Defensive industries. In bad times, Return and Valuation matter the most across both groups. In sum, our results suggest that a limited number out of the 73 characteristics conveys the most informative signals for the cross-section of industries and throughout the business cycle. Investors can exploit them for asset rebalancing strategies, conditional on the economic and financial environment.

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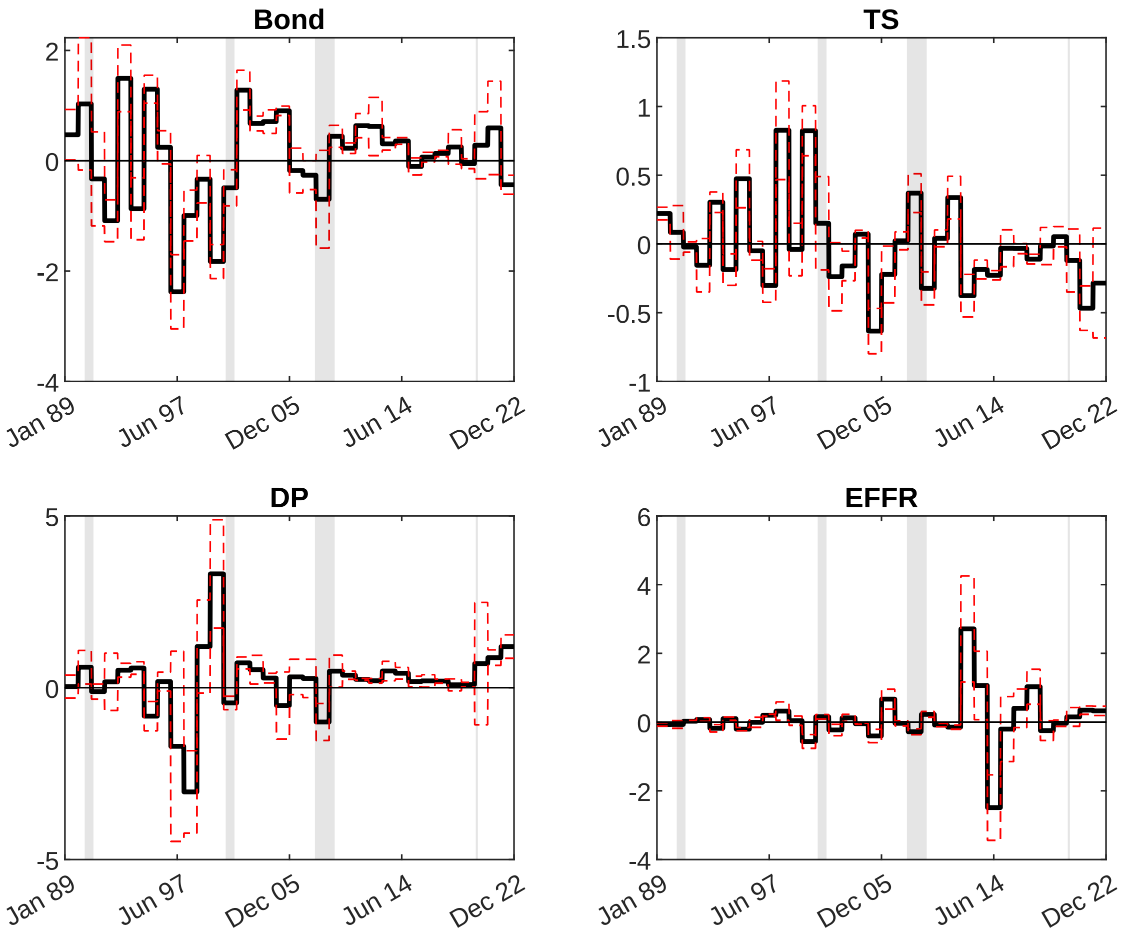
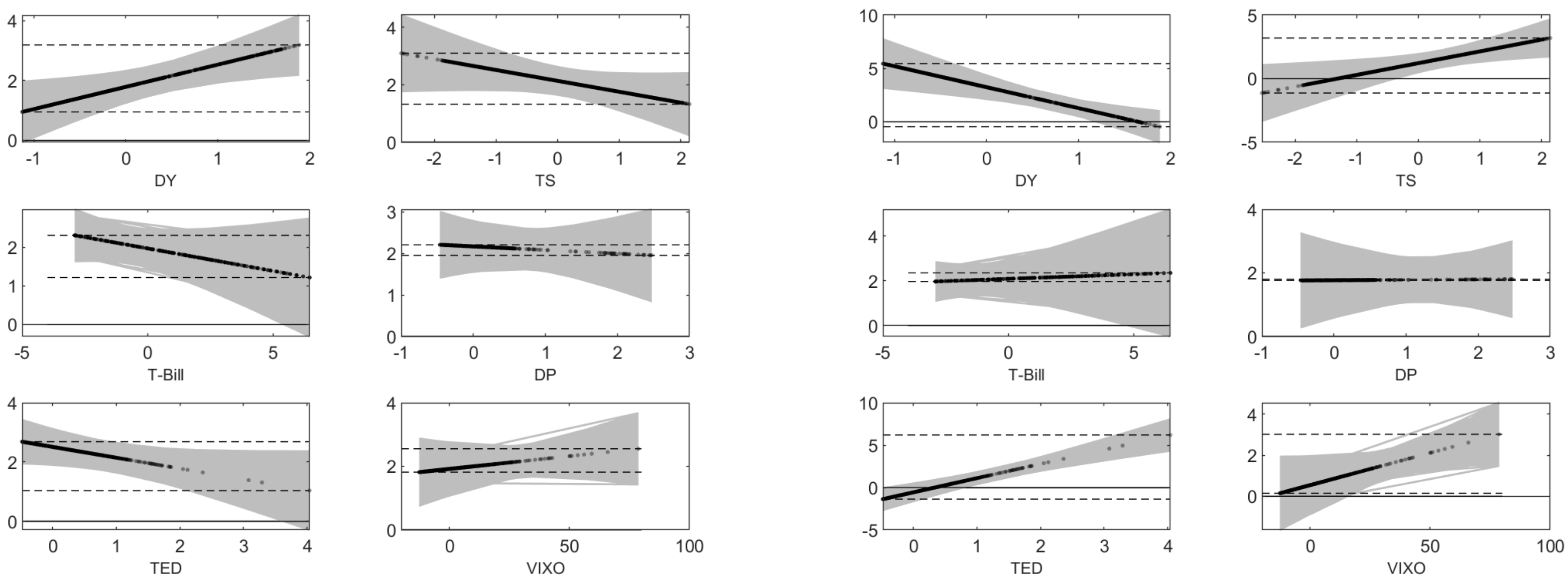


Figure 1. Each panel of the plot shows the slope coefficients for the state variables in moving-window predictive regressions of three years ahead OF market portfolio returns. The state variables are proxied by the long-term bond's cumulative returns, Term Spread, Default Premium, and Effective Federal Fund Rate. The dotted red lines show the 95% conditional confidence intervals, which are estimated using Newey-West standard errors. The shaded areas depict the NBER recession periods. The sample period is from January 1986 to December 2022 at the weekly frequency, and regression windows are one year.



(a) Market risk **(b)** Default Premium risk

Figure 2. The figure plots the price of market risk, estimated from a specification of ICAPM which assumes that $\gamma_j = 0, \ \forall\ j$, (shown in Panel a), and the price of Default Premium risk, (shown in Panel b) estimated from a specification of ICAPM which assumes that $\gamma_{\Delta \text{DP}} \neq 0$, conditional on one information variable. The Default Premium risk is estimated from the covariation of asset returns with the innovations in the Default Premium. Each panel represents the results using the lagged and demeaned values of the US market dividend yield (DY), term spread (TS), the short-term interest rate (T-Bill), Default Premium (DP), TED spread (TED), and the VIX Index (VIXO) as the information variable. The 95% conditional confidence intervals are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. The dotted lines show the maximum and minimum values of the estimated prices of risk. The sample period is from January 1986 to December 2022 at the weekly frequency.

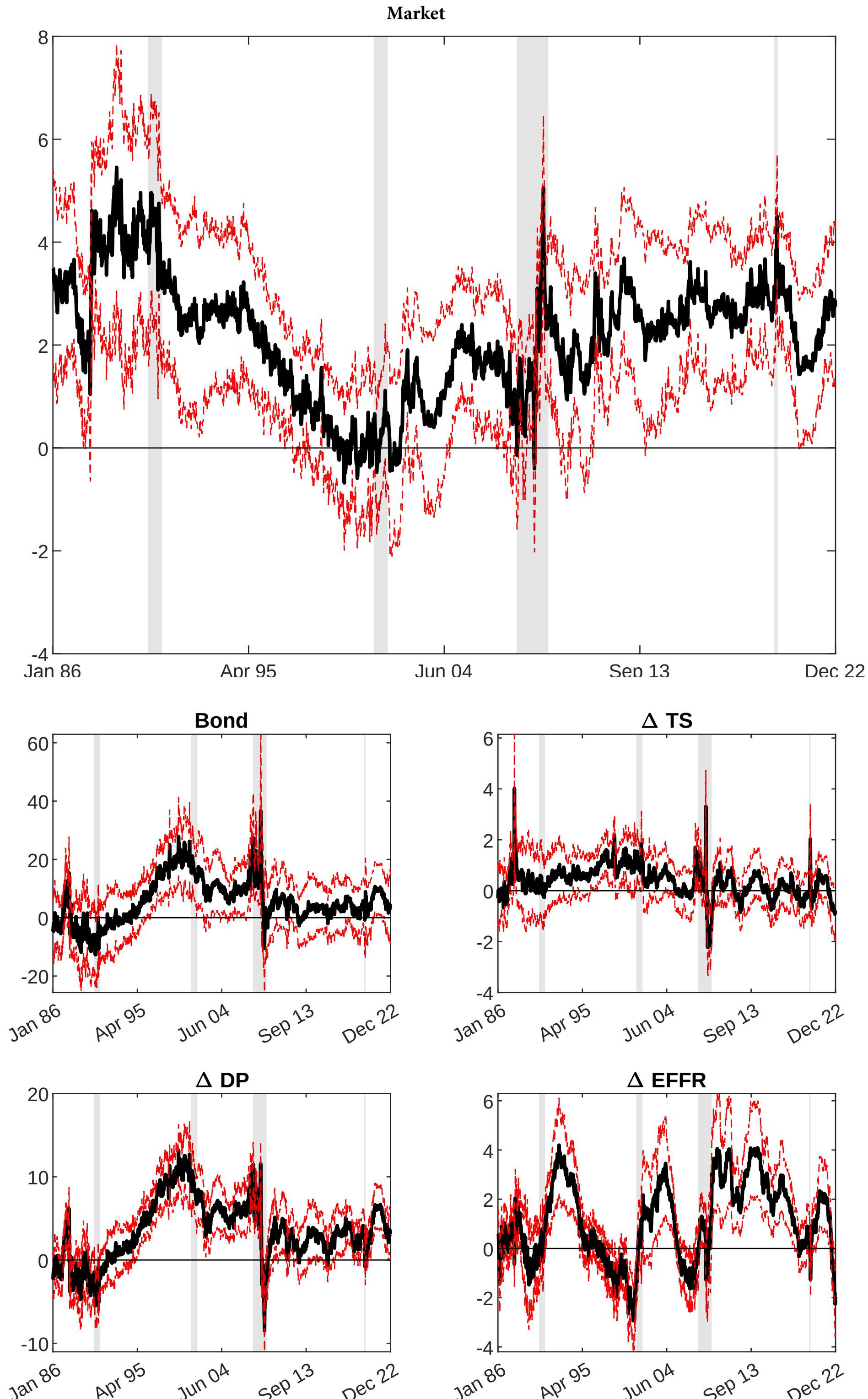
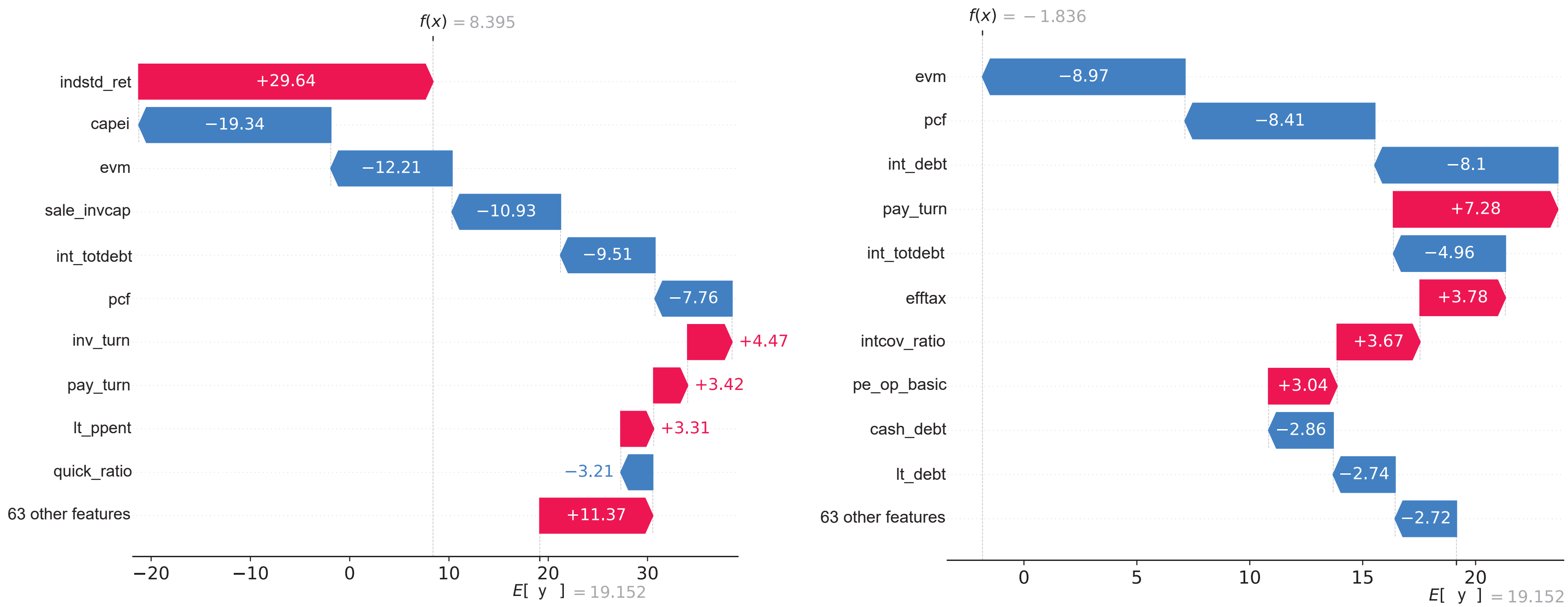


Figure 3. The top plot shows the time-varying price of market risk, estimated from a specification of the ICAPM which assumes that $\gamma_j = 0, \ \forall\ j$, conditional on all information variables. Each panel of the bottom plot shows the time-varying price of intertemporal risk, as proxied by the long-term bond return, innovations in the Term Spread, innovations in the Default Premium, and innovations in the Effective Federal Fund Rate. These are estimated from a specification of ICAPM which assumes that $\gamma_{\Delta\text{Bond}} \neq 0$, $\gamma_{\Delta\text{TS}} \neq 0$, $\gamma_{\Delta\text{DP}} \neq 0$, and $\gamma_{\Delta\text{EFFR}} \neq 0$, respectively, conditional on all information variables. The dotted red lines show the 95% conditional confidence intervals, which are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. The shaded areas depict the NBER recession periods. The sample period is from January 1986 to December 2022 at the weekly frequency.



(a) March 15, 2009 **(b)** March 17, 2019

Figure 4. The figure plots the SHAP values of the top 10 features for the Trading industry's risk premia on March 15, 2009, and March 17, 2019. $E[y]$ denotes the mean of the asset risk premia in our sample, which are estimated from the ICAPM model with all the macro state risk proxies, including the innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR). $f(x)$ denotes the outcome of the XGBoost model with all features on that date. SHAP values are measured based on the output of the XGBoost model. For the sake of better readability, weekly SHAP values are multiplied by 10,000.

Table 1. The table reports summary statistics for the test assets, the state variables risk proxies in the asset pricing models, and the information variables. Panel A reports average ($\overline{\text{Exp.}}$, $\overline{\text{Rec.}}$), and standard deviation ($\sigma^{\text{Exp.}}$, $\sigma^{\text{Rec.}}$) values of the annualized weekly returns of the 49 Industry portfolios, averaged per industry groups and over 1773 expansion and 157 recession weeks. It also reports its correlations (ρ) with the state variables proxies, which include the market return, the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR). Panel B reports the summary statistics for these state variables over the whole sample. Panel C provides the summary statistics over the whole sample on the US market dividend yield (DY), Term Spread (TS), the short-term interest rate (T-Bill), Default Premium (DP), TED spread (TED), and the VIX Index (VIXO) as conditioning information variables. In estimation we use their lagged and demeaned values. The sample period is from January 1986 to December 2022 at the weekly frequency.

Panel A	$\overline{\text{Exp.}}$	$\overline{\text{Rec.}}$	$\sigma^{\text{Exp.}}$	$\sigma^{\text{Rec.}}$	ρ^{Market}	ρ^{Bond}	$\rho^{\Delta\text{TS}}$	$\rho^{\Delta\text{DP}}$	$\rho^{\Delta\text{EFFR}}$
Defensive	0.141	-0.028	1.479	2.421	0.572	-0.004	-0.029	-0.042	-0.022
Cyclical	0.153	-0.228	1.536	3.337	0.781	-0.119	0.054	-0.072	-0.051
Sensitive	0.155	-0.202	1.654	2.989	0.734	-0.139	0.064	-0.079	-0.040
Others	0.124	-0.239	1.343	2.593	0.829	-0.117	0.034	-0.070	-0.050
Panel B	$\overline{\text{ALL}}$	σ	Min	Max	ρ^{Market}	ρ^{Bond}	$\rho^{\Delta\text{TS}}$	$\rho^{\Delta\text{DP}}$	$\rho^{\Delta\text{EFFR}}$
Market	0.114	1.237	-9.344	6.561					
Bond	0.056	0.505	-2.052	4.364	-0.120				
ΔTS	-0.001	0.100	-0.480	0.590	0.044	-0.560			
ΔDP	0.000	0.051	-0.390	0.720	-0.079	0.068	-0.047		
ΔEFFR	-0.002	0.176	-1.290	1.690	-0.060	-0.057	-0.122	0.021	
Panel C	$\overline{\text{ALL}}$	σ	Min	Max	ρ^{DY}	ρ^{TS}	$\rho^{\text{T-Bill}}$	ρ^{DP}	ρ^{TED}
DY	2.179	0.669	1.054	4.065					
TS	1.359	1.023	-1.180	3.500	0.113				
T-Bill	2.903	2.482	0.000	9.367	0.381	-0.505			
DP	0.974	0.368	0.510	3.450	0.381	0.210	-0.191		
TED	0.539	0.431	0.060	4.580	0.474	-0.221	0.527	0.335	
VIXO	20.064	8.839	7.540	98.810	0.126	0.072	0.043	0.559	0.467

Table 2. The table reports slope coefficients for the prices of risk from various ICAPM models, conditional on one information variable at a time. Panel A reports the estimations for the price of market risk, from a specification of ICAPM which assumes that $\gamma_j = 0, \ \forall \ j$. Panels B to E report the estimations for the prices of intertemporal risk from the ICAPM with the market and one state risk proxy, such as the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), or innovations in the Effective Federal Fund Rate (ΔEFFR). Each column represents the regression results using one information variable, which is the lagged and demeaned values of the US market dividend yield (DY), Term Spread (TS), the short-term interest rate (T-Bill), Default Premium (DP), TED spread (TED), and the VIX Index (VIXO). P-values are estimated using GLS standard errors (reported in parenthesis) corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 1986 to December 2022 at the weekly frequency.

	DY	TS	T-Bill	DP	TED	VIXO
Panel A: Market						
Level	1.788***	2.135***	1.973***	2.165***	2.511***	1.917***
	(0.272)	(0.244)	(0.251)	(0.310)	(0.308)	(0.424)
Interaction	0.744**	-0.378	-0.117	-0.086	-0.364*	0.008
	(0.300)	(0.240)	(0.105)	(0.282)	(0.202)	(0.011)
Panel B: Bond						
Level	4.912**	3.521*	4.329**	4.268**	4.703**	4.836**
	(2.067)	(1.876)	(1.965)	(2.015)	(2.120)	(2.217)
Interaction	-5.614***	-0.630	0.455	-4.128	-0.158	-0.123
	(2.175)	(2.034)	(0.769)	(3.670)	(2.335)	(0.088)
Panel C: ΔTS						
Level	0.001	-0.108	-0.246	-0.412*	-0.194	-0.256
	(0.194)	(0.188)	(0.199)	(0.217)	(0.202)	(0.233)
Interaction	0.722***	0.161	-0.181**	1.038***	0.112	0.026***
	(0.255)	(0.186)	(0.081)	(0.239)	(0.191)	(0.009)
Panel D: ΔDP						
Level	3.248***	1.223***	2.083***	1.770***	-0.570	0.539
	(0.566)	(0.362)	(0.429)	(0.599)	(0.532)	(0.717)
Interaction	-1.965***	0.925**	0.041	0.013	1.674***	0.031*
	(0.589)	(0.370)	(0.179)	(0.396)	(0.320)	(0.017)
Panel E: ΔEFFR						
Level	-0.159	0.043	0.101	0.200	0.183	0.124
	(0.218)	(0.182)	(0.184)	(0.204)	(0.246)	(0.296)
Interaction	0.303	0.307	-0.061	-0.523	-0.144	-0.003
	(0.232)	(0.218)	(0.073)	(0.320)	(0.189)	(0.007)

Table 3. The table reports the p-values for the prices of risk from various ICAPM models, conditional on all information variables. For each risk factor, we report the p-values of a Wald test for the null hypothesis of zero prices of risk in the first row as well as for the null hypothesis of constant prices of risk in the second row. We also report in the third row the p-values for a two-tailed test of means of these time-varying prices of risk and their estimates from a constant price of risk model specification, tabulated in Table A5. Column 1 reports these values for the market model, which assumes that $\gamma_j = 0,\ \forall\ j$. Columns 2 to 5 report them for the ICAPM model with one state risk proxy, including the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Funds Rate (ΔEFFR). Column 6 reports the p-value for the model that includes all the macroeconomic risk proxies. P-values are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. The sample period is from January 1986 to December 2022 at the weekly frequency.

	(1)	(2)	(3)	(4)	(5)	(6)
$H_0: \lambda_t = const.$	0.000	0.001	0.000	0.011	0.000	0.017
$H_0: \lambda_t = 0$	0.000	0.000	0.000	0.000	0.000	0.000
$H_0: \overline{\lambda_t} = \widehat{\lambda}$	0.910	0.264	0.390	0.507	0.666	0.879
$H_0: \gamma_{\text{Bond},t} = const.$		0.014				
$H_0: \gamma_{\text{Bond},t} = 0$		0.002				
$H_0: \overline{\gamma_{\text{Bond},t}} = \widehat{\gamma_{\text{Bond}}}$		0.216				
$H_0: \gamma_{\Delta\text{TS},t} = const.$			0.000			0.002
$H_0: \gamma_{\Delta\text{TS},t} = 0$			0.001			0.003
$H_0: \overline{\gamma_{\Delta\text{TS},t}} = \widehat{\gamma_{\Delta\text{TS}}}$			0.031			0.048
$H_0: \gamma_{\Delta\text{DP},t} = const.$				0.000		0.000
$H_0: \gamma_{\Delta\text{DP},t} = 0$				0.000		0.000
$H_0: \overline{\gamma_{\Delta\text{DP},t}} = \widehat{\gamma_{\Delta\text{DP}}}$				0.000		0.000
$H_0: \gamma_{\Delta\text{EFFR},t} = const.$					0.000	0.000
$H_0: \gamma_{\Delta\text{EFFR},t} = 0$					0.000	0.000
$H_0: \overline{\gamma_{\Delta\text{EFFR},t}} = \widehat{\gamma_{\Delta\text{EFFR}}}$					0.000	0.000

Table 4. The table reports the changes in the prices of risk during the business cycle. In Panel A, we report the mean values over time ($\overline{\text{ALL}}$) for each risk factor, estimated from various ICAPM models conditional on all information variables. We also report the difference in these values during the NBER recession and expansion periods ($\overline{\text{Rec.}} - \overline{\text{Exp.}}$), as well as the p-values for a two-tailed test of means over these periods ($H_0 : \overline{\text{Rec.}} = \overline{\text{Exp.}}$). In Panel B, we report the slope coefficients from regressions of the prices of risk on a time trend interacted with an NBER recession dummy. Column 1 reports these estimates for a specification of ICAPM which assumes that $\gamma_j = 0, \ \forall \ j$. Columns 2 to 5 report them for the ICAPM model with one state risk proxy, including the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR). Column 6 reports the p-value for the model that includes all the macroeconomic risk proxies. P-values are estimated using Newey-West standard errors. The sample period is from January 1986 to December 2022 at the weekly frequency.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Level						
$\overline{\lambda_{\text{ALL}}}$	2.130	2.513	1.868	2.893	2.222	2.741
$\overline{\lambda_{\text{Rec.}}} - \overline{\lambda_{\text{Exp.}}}$	-0.102	-0.114	0.079	-0.292	-0.147	-0.195
$H_0 : \overline{\lambda_{\text{Rec.}}} = \overline{\lambda_{\text{Exp.}}}$	0.441	0.285	0.597	0.000	0.276	0.005
$\overline{\gamma_{\text{Bond,ALL}}}$		5.762				
$\overline{\gamma_{\text{Bond,Rec.}}} - \overline{\gamma_{\text{Bond,Exp.}}}$		2.053				
$H_0 : \overline{\gamma_{\text{Bond,Rec.}}} = \overline{\gamma_{\text{Bond,Exp.}}}$		0.029				
$\overline{\gamma_{\Delta\text{TS,ALL}}}$			-0.434			-0.403
$\overline{\gamma_{\Delta\text{TS,Rec.}}} - \overline{\gamma_{\Delta\text{TS,Exp.}}}$			0.426			0.406
$H_0 : \overline{\gamma_{\Delta\text{TS,Rec.}}} = \overline{\gamma_{\Delta\text{TS,Exp.}}}$			0.000			0.000
$\overline{\gamma_{\Delta\text{DP,ALL}}}$				3.571		3.726
$\overline{\gamma_{\Delta\text{DP,Rec.}}} - \overline{\gamma_{\Delta\text{DP,Exp.}}}$				-0.946		-1.123
$H_0 : \overline{\gamma_{\Delta\text{DP,Rec.}}} = \overline{\gamma_{\Delta\text{DP,Exp.}}}$				0.036		0.011
$\overline{\gamma_{\Delta\text{EFFR,ALL}}}$					1.106	1.112
$\overline{\gamma_{\Delta\text{EFFR,Rec.}}} - \overline{\gamma_{\Delta\text{EFFR,Exp.}}}$					-0.898	-0.656
$H_0 : \overline{\gamma_{\Delta\text{EFFR,Rec.}}} = \overline{\gamma_{\Delta\text{EFFR,Exp.}}}$					0.000	0.000
Panel B: Growth Rate						
λ_t : Rec.	0.234***	0.210***	0.354***	-0.048**	0.249***	0.082***
$\gamma_{\text{Bond},t}$: Rec.		-1.850***				
$\gamma_{\Delta\text{TS},t}$: Rec.			0.330***			0.311***
$\gamma_{\Delta\text{DP},t}$: Rec.				-1.234***		-1.222***
$\gamma_{\Delta\text{EFFR},t}$: Rec.					0.024	0.124***

Table 5. The table reports the contribution of each risk factor to the total asset risk premia. Panel A presents the mean values of the sum of absolute factors' contributions, over all industries and time ($\overline{\text{ALL}}$). It also reports the difference in these values during the NBER recession and expansion periods ($\overline{\text{Rec.}} - \overline{\text{Exp.}}$), as well as the p-values for a two-tailed test of equality in means over these periods ($H_0 : \overline{\text{Rec.}} = \overline{\text{Exp.}}$). The panel also reports the slope coefficients from regressions of the factor contributions of risk factors on a time trend interacted with an NBER recession dummy (FC:Rec.). Panel B presents the mean values of the sum of absolute factors' contributions over the whole sample by industry groups: Defensive ($\overline{\text{Def.}}$), Cyclical ($\overline{\text{Cycl.}}$), Sensitive ($\overline{\text{Sens.}}$) and Others ($\overline{\text{Othr.}}$). It also reports the difference in these values for Cyclical and Defensive industries ($\overline{\text{Def.}} - \overline{\text{Cycl.}}$), as well as the p-values for a two-tailed test of equality in means over these groups ($H_0 : \overline{\text{Def.}} = \overline{\text{Cycl.}}$). The asset risk premia are estimated from the ICAPM model with all the macro state risk proxies, including the innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR). P-values are estimated using Newey-West standard errors. The sample period is from January 1986 to December 2022 at the weekly frequency.

	Market	ΔTS	ΔDP	ΔEFFR
Panel A: Business Cycle				
$\overline{\text{ALL}}$	0.552	0.095	0.235	0.118
$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	-0.015	-0.018	0.084	-0.050
$H_0 : \overline{\text{Rec.}} = \overline{\text{Exp.}}$	0.000	0.000	0.000	0.000
FC:Rec.	1.968***	0.762***	-2.644***	-0.087
Panel B: Industry Group				
$\overline{\text{Def.}}$	0.535	0.102	0.243	0.119
$\overline{\text{Cycl.}}$	0.557	0.092	0.230	0.120
$\overline{\text{Sens.}}$	0.551	0.094	0.236	0.119
$\overline{\text{Othr.}}$	0.574	0.094	0.227	0.104
$\overline{\text{Def.}} - \overline{\text{Cycl.}}$	-0.022	0.010	0.013	0.000
$H_0 : \overline{\text{Def.}} = \overline{\text{Cycl.}}$	0.000	0.000	0.000	0.702

Table 6. The table reports the prediction performance metrics for ten machine learning techniques, adopted to predict the risk premia for industry portfolios. These metrics are the coefficient of determination over the training set (R^2_{in}) and test set (R^2_{POS}), mean absolute prediction error (MAPE), and root mean squared prediction error (RMSPE). MAPE and RMSPE values are multiplied by 100 for better readability. We consider six linear regressions with dimension reduction, including ordinary least squares (LS), least absolute shrinkage and selection operator (LASSO), Ridge (Ridge), elastic net (ElasticNet), principal component analysis in conjunction with least squares (PCR), and partial least squares (PLS). We also consider three decision tree models, including random forest regressions (RFR), gradient-boosted regression trees (GBRT), and extreme gradient boosting (XGBoost) method. Lastly, we consider Multi-layer Perceptron (MLP) neural networks. The sample period is from January 1986 to December 2022 at the weekly frequency.

	R^2_{in}	R^2_{POS}	MAPE	RMSPE
LS	0.188	0.136	0.162	0.312
LASSO	0.182	0.133	0.161	0.313
Ridge	0.188	0.136	0.162	0.312
ElasticNet	0.185	0.135	0.161	0.313
PLS.	0.173	0.122	0.163	0.315
PCR	0.163	0.113	0.164	0.317
RFR	0.567	0.403	0.127	0.260
GBRT	0.542	0.404	0.124	0.260
XGBoost	0.761	0.539	0.088	0.228
MLP	0.287	0.204	0.150	0.300

Table 7. The table presents the aggregated SHAP values of feature contributions to the industries' risk premia. Panel A presents the means of the sum of absolute SHAP values, measured based on the output of the XGBoost model, per characteristics category, over all industries and time ($\overline{\text{ALL}}$). It also reports the difference in these values during the NBER recession and expansion periods ($\overline{\text{Rec.}} - \overline{\text{Exp.}}$), as well as the p-values for a two-tailed test of equality in means over these periods ($H_0 : \overline{\text{Rec.}} = \overline{\text{Exp.}}$). Row SHAP:Rec. reports the slope coefficients from regressions of these SHAP values on a time trend interacted with an NBER recession dummy. Panel B presents the means over the sample period of the sum of absolute SHAP values per characteristics category over industry groups: Defensive ($\overline{\text{Def.}}$), Cyclical ($\overline{\text{Cycl.}}$), Sensitive ($\overline{\text{Sens.}}$) and Others ($\overline{\text{Othr.}}$). It also reports the difference in these values for Cyclical and Defensive ($\overline{\text{Def.}} - \overline{\text{Cycl.}}$) industries, as well as the p-values for a two-tailed test of equality in means over these groups ($H_0 : \overline{\text{Def.}} = \overline{\text{Cycl.}}$). For the sake of better readability, weekly SHAP values are multiplied by 10,000. P-values are estimated using New West standard errors. The sample period is from January 1986 to December 2022 at the weekly frequency.

	ΣReturn	ΣValuation	ΣProfitability	ΣEfficiency	ΣFinancial Soundness	ΣCapitalization	ΣSolvency	ΣLiquidity	ΣOther
Panel A: Business Cycle									
$\overline{\text{ALL}}$	10.234	36.212	9.046	14.068	17.455	1.764	3.631	4.935	0.987
$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	5.228	4.398	-0.106	1.384	-0.061	-0.109	-0.161	0.096	-0.062
$H_0 : \overline{\text{Rec.}} = \overline{\text{Exp.}}$	0.000	0.000	0.000	0.000	0.187	0.000	0.000	0.000	0.000
SHAP:Rec.	1.542***	1.298***	0.078***	0.445***	0.232***	-0.046***	0.018**	0.040***	0.004**
Panel B: Industry									
$\overline{\text{Def.}}$	13.000	33.298	7.307	12.285	14.998	0.234	3.340	4.809	1.170
$\overline{\text{Cycl.}}$	9.547	35.980	7.260	11.351	16.604	0.157	2.974	4.213	0.939
$\overline{\text{Sens.}}$	9.842	35.522	7.316	11.729	15.823	0.206	3.195	3.987	0.966
$\overline{\text{Othr.}}$	7.851	35.948	7.009	12.558	15.291	0.124	2.682	3.938	0.819
$\overline{\text{Def.}} - \overline{\text{Cycl.}}$	3.452	-2.682	0.047	0.934	-1.605	0.076	0.366	0.595	0.231
$H_0 : \overline{\text{Def.}} = \overline{\text{Cycl.}}$	0.000	0.000	0.019	0.000	0.000	0.000	0.000	0.000	0.000

Online Appendix

A Asymmetric Dynamic Conditional Correlation

For the estimation of the conditional second moments, we implement the Asymmetric Dynamic Conditional Correlation (ADCC) specification proposed by Cappiello et al. (2006), where we allow for a leverage effect in the variance dynamic through GJR-GARCH and asymmetry in correlation (Longin and Solnik, 2001; Ang and Bekaert, 2002) to capture higher comovements in market downturns that are at times associated with recessions. ADCC enables us to capture the asymmetric dynamics both in volatility and in correlations.[25] Formally, we first take out any autoregressive elements in the returns of each asset and filter them with a univariate asymmetric GARCH model (Glosten, Jagannathan, and Runkle, 1993):

$$\begin{aligned} R_t &= \phi_0 + \phi_1 R_{i,t-1} + u_t, \\ \sigma_t^2 &= \omega + \beta\sigma_{t-1}^2 + (\alpha + \delta I\left[u_{t-1} < 0\right])\ u_{t-1}^2 \\ u_t &\sim N\left(0, s_t\right) \end{aligned} \tag{A1}$$

Where, $I(\cdot)$ denotes the indicator function; ϕ_0, ϕ_1 are the autoregressive coefficients; ω, α, β are the GARCH parameters; δ captures the "leverage effect". In this setting, σ_t^2 denotes the conditional variance of assets, derived by conditioning on the previous assets' returns.

In the second step, we compute estimates of the bivariate conditional correlations between each asset return and the market portfolio, with a scalar ADCC filter. Concatenate standardized return of asset i and market portfolio to form matrix $\boldsymbol{\varepsilon_t}$ and set $\overline{\rho} = E[\varepsilon_t \varepsilon^{'}]$ the unconditional correlation of asset pairs. Then the 2×2 Matrix $\boldsymbol{\rho_t}$ below generates the conditional correlations between each asset pair.

$$\begin{aligned} Q_t &= \left(\overline{\rho} - \mathrm{a}^2\overline{\rho} - \mathrm{b}^2\overline{\rho} - \mathrm{g}^2\overline{N}\right) \ + a^2\boldsymbol{\varepsilon_{t-1}}\boldsymbol{\varepsilon'_{t-1}} + \mathrm{g}^2 n_{t-1}n'_{t-1} \ + \ b^2 Q_{t-1} \\ \boldsymbol{\rho_t} &= \ diag(Q_t)^{-\frac{1}{2}} \ \ Q_t \ \ diag(Q_t)^{-\frac{1}{2}} \\ n_t &= I\left[\mathbf{e}_t < 0\right] \ .* \ \mathbf{e_t} \end{aligned} \tag{A2}$$

where $I(\cdot)$ denotes the indicator function and $.*$ denotes the Hadamard or element by element matrix multiplication. A necessary and sufficient condition for Q_t to be positive definite is that $\mathrm{a}^2 + \mathrm{b}^2 + \delta\mathrm{g}^2 < 1$, where $\delta = \max(eigenvalue[\ \overline{\rho}^{-\frac{1}{2}}\overline{N}\overline{\rho}^{-\frac{1}{2}}]$.

As the assumption of conditional normality is often violated in stock returns, in both steps we use the Quasi-Maximum Likelihood Estimator (QMLE) that is consistent and asymptotically normal. For multivariate GARCH models, Bollerslev and Wooldridge (1992) show that this estimator is consistent as long as the first two moment equations are correctly specified. After estimating the conditional correlations, we compute the variance-covariance matrix of assets, $D_t\boldsymbol{\rho}_t D_t$, choosing D_t as a diagonal matrix of conditional standard deviations with $s_{i,t}$ and $s_{m,t}$ on the diagonal and zeroes elsewhere.

The ADCC estimation results show supportive evidence in favor of asymmetric volatility and asymmetric correlations, albeit with weaker statistical support for the latter, since the parameter for correlation asymmetry, g, is only significant for half of the asset pairs. The estimated correlations of industry portfolios with the market portfolio are indeed higher during recession periods when

[25] Volatility of a firm may increase after a negative shock due to effects like leverage effect or volatility feedback. The leverage of a firm (debt-to-equity ratio) increases after a negative shock to the stock value. Thus, the volatility of the whole firm, which is assumed to remain constant, must be reflected by an increase in volatility in the non-leveraged part of the firm (equity). Similarly, correlations may increase following negative systematic shocks that induce downward pressure on the returns of any pairs of stocks.

most market downturns occur. The cross-sectional average of the conditional correlations is 0.72 in recessions and 0.68 in expansions. Summary statistics of the conditional covariances computed from the ADCC filter between each industry index and the aggregate market, as well as the proxies of intertemporal risk, are in Table A4. On average, assets show a larger covariance with the market portfolio with an average of 5.51. Those with long-term bond returns, the innovations in the Effective Federal Fund rate, and in the Default Premium are negative whereas the average of the covariances with the innovations in the Term Spread is positive but substantially smaller than the one with the market (0.80). Among all risk factors, the covariances of asset returns with the Term Spread risk have the largest standard deviation at 6.72 and the covariances with the long-term Bond risk have on average the lowest volatility. The covariances of the intertemporal risk factors are also larger in absolute terms in recession periods, a finding that aligns with the evidence on market covariances.

B Constant Price of Risk

To compare our results to previous research and to establish a benchmark for our time-varying analysis, Table A5 reports results of the unconditional models for the ICAPM under different specifications. The price of market risk is positive and significant, with point estimates in a range between 2.081 to 2.714 among all models. These coefficients on the market risk-return tradeoff are somewhat lower than the one reported in Bali (2008). However, we find that our estimates would be in line with his magnitude when using a cross-section that excludes the market portfolio as in that paper. When we proxy the intertemporal risk through the bond returns, we find a positive price of risk that in our test is marginally significant, in contrast with the lack of statistical evidence in Scruggs and Glabadanidis (2003) and Gerard and Wu (2006). When we proxy the intertemporal risk using the innovations in the macro-variables one at a time, the evidence shows a significant price for the Default Premium but not for the Effective Federal Fund Rate or the Term Spread risk. Furthermore, the significance for the Default Premium survives when we consider all the innovations in the same regression. Including the intertemporal factors does not change the statistical significance of the market price of risk in all the ICAPM regressions.

C Interaction models and conditional variances

Filtering the price of risks with interaction models would involve estimating the system below, assuming a one-factor asset pricing model:

$$R_{i,t}-r_{f,t}=\beta_0+\beta_1 cov_{t-1}\left(R_{i,t},r_{m,t}\right)+\beta_2\ \mathrm{IV}_{t-1}+\beta_3\ \mathrm{IV}_{t-1}cov_{t-1}\left(R_{i,t},r_{m,t}\right)+\epsilon_{i,t} \tag{A3}$$

In this setting, the conditional price of market risk,λ_t, is the derivative of the left-hand side with respect to the regressand. Thus, we have:

$$\lambda_t=\left(\frac{\partial R_i}{\partial cov}\,\middle|\, IV\right)=\beta_1+\beta_3 IV \tag{A4}$$

$$var\left(\frac{\partial R_i}{\partial cov}\,\middle|\, IV\right)=var\left(\beta_1\right)+IV^2 var\left(\beta_3\right)+2IV cov\left(\beta_1,\beta_3\right) \tag{A5}$$

Conditioning is done on a set of K information variables, $IV=[IV_1,\ldots,IV_{\mathrm{K}}]$. As a result, we have $\beta_3=[\beta_{3,1},\ldots,\beta_{3,\mathrm{K}}]$. So the extended version of the above formula becomes:

$$var\left(\frac{\partial R_i}{\partial cov}\middle| IV\right) = var\left(\beta_1\right) + IV_1 cov\left(\beta_1, \beta_{3,1}\right) + \cdots + IV_{\mathrm{K}} cov\left(\beta_1, \beta_{3,\mathrm{K}}\right)$$
$$+ IV_1 cov\left(\beta_{3,1}, \beta_1\right) + IV_1^2 var\left(\beta_{3,1}\right) + \cdots + IV_1 IV_K cov\left(\beta_{3,1}, \beta_{3,K}\right)$$
$$+ \ldots$$
$$+ IV_{\mathrm{K}} cov\left(\beta_{3,K}, \beta_1\right) + IV_{\mathrm{K}} IV_1 cov\left(\beta_{3,\mathrm{K}}, \beta_{3,1}\right) \cdots + IV_{\mathrm{K}}^2 var\left(\beta_{3,K}\right) \tag{A6}$$

D Estimating the Machine Learning Techniques

We follow the approach of Gu et al. (2020), Bali et al. (2023), and Leippold et al. (2022), and identify the structural relationship between the dependent and the explanatory variables based on the predictive performance of a set of advanced estimation techniques. The structural relationship $f(.)$ is then inferred from this technique. More formally, we consider the following:

$$\begin{aligned} y &= f_{\{i,\Theta\}}(X) + u \\ E\left[u|X\right] &= 0, \quad u \sim iid \end{aligned} \tag{A7}$$

Where the dependent variable y is a vector of $M \times 1$ observations of industry risk premia that are implied from Equation (2) for $N \times T$ industry-week estimates. Our analysis covers 49 industry portfolios over 1930 weeks, resulting in 94,570 industry-week observations. The explanatory variables X (also referred to as features) is a matrix of $M \times K$ lagged industry characteristics, with $K = 73$ (see Section 3 for the list of these variables). $f_{\{i,\Theta\}}$ represents the machine learning operator i, with learnable parameter set Θ. The number of parameters to be estimated depends on the specifications of each operator. These parameters are chosen by minimizing the mean square forecast error in the training set, using the regularization term, $R(.)$, and hyperparameter, λ, which is chosen using the validation set:

$$\min_{\Theta} \sum_{m=1}^{M} \Big(y_m - f_{\{i,\Theta\}}\left(X_m\right)\Big)^2 - \lambda\ R\left(f_{\{i,\Theta\}}\right) \tag{A8}$$

More specifically, we consider the following ten commonly used machine learning techniques: ordinary least squares (LS), least absolute shrinkage and selection operator (LASSO), Ridge (Ridge), elastic net (ElasticNet), principal component analysis in conjunction with least squares (PCR), and partial least squares (PLS). We also consider three decision tree models, including random forest regressions (RFR), gradient-boosted regression trees (GBRT), and extreme gradient boosting (XGBoost) methods. Lastly, we consider Multi-layer Perceptron (MLP) neural networks. These are characterized by a set of learnable parameters, Θ, and hyperparameters, Λ_{ML}. The structural relationship, implied by each technique i, is thus represented by $f_{\{i,\Theta,\Lambda_{ML}\}}(.)$.

In the linear models, LASSO and Ridge regressions choose L_1 and L_2 norms of the slope coefficients as the regularization terms, respectively, to reduce the multicollinearity in the feature set, whereas ElasticNet uses the linear combination of L_1 and L_2.[26,27] PCR involves first reducing the dimension of the explanatory variables by extracting the principal components of the features. Then it includes a least square estimation using these principal components. PLS is essentially

[26] Their general forms are $L_1 = \sum_{k=1}^{K} |\beta_k| \leq c$ and $L_2 = \sum_{k=1}^{K} \beta_k^2 \leq c$, where β_k is the slope coefficient for feature k and c is the threshold constant.

[27] See Diebold and Shin (2019) for more details and application of these techniques in finance

similar to this technique, but unlike PCR, which focuses on the variance of the features, it incorporates the information content of the correlation between the dependent variable and the features to reduce dimensionality.

The various dimension reduction approaches discussed above reduce the multicollinearity issues often observed in datasets of highly correlated features, such as ours. For example, in Figure A6, which presents the cross-correlations of the industry characteristics in our study, the following pairs have an absolute correlation above 0.90: {*debt_at; capital_ratio*}, {*dltt_be; debt_invcap*}, {*cash_lt; cash_ratio*}, {*cfm; npm*}, {*debt_capital; debt_assets*}, {*aftret_eq; aftret_equity*}, {*debt_invcap; capital_ratio*}, {*equity_invcap; capital_ratio*}, {*opmad; npm*}, {*op- mbd; npm*}, {*pe_exi; pe_inc*}, {*profit_lct; ocf_lct*}, {*ptpm; npm*}, {*quick_ratio; cash_ratio*}, {*roce; roe*}, {*sale_invcap; at_turn*}, {*totdebt_invcap; capital_ratio*}. For this reason, once we are reporting the aggregated SHAP value results in Table 7, we exclude features that are highly correlated, to avoid double counting.

Differently from the ordinary least square model, the tree-based ones are minimally affected by high correlations among features. In these models, in each decision tree, the explanatory variables are divided into homogeneous subsamples, s, by recursive binary splitting, such that the mean squared errors (MSE) in the adjacent regions are minimized.

$$\min_{s} \left[\text{MSE } (y|x_k \leq s) \; + \; \text{MSE } (y|x_k \geq s) \; \right] \tag{A9}$$

Then in each region, a piece-wise linear relationship is fitted between the dependent and explanatory variables, often in the form of a mean function. This approach accommodates a more general, even nonlinear, form relationship between these variables throughout the whole sample. RFR involves a bootstrapping procedure on an ensemble of decision trees (Breiman, 2001). GBRT instead searches for the optimal decision tree, using an iterative algorithm that improves the model's predictions by focusing on the samples that were poorly predicted in the previous iterations. XGBoost is a high-performance implementation of gradient boosting framework which incorporates both L_1 and L_2 regularization terms in the objective function.

Lastly, we execute a class of feed-forward neural network called Multi-layer Perceptron (MLP), which implements several nonlinear layers to incorporate nonlinearity in the functional form between explanatory and dependent variables.

For the machine learning technique selection, we divide our sample into three subsets: training, validation, and test sets. Since our focus is to identify the key drivers of the asset risk premia, which we estimated using the whole sample through a GARCH specification, we use a random assignment approach. This further ensures that the estimations and tests of the machine learning models are based on subsets that follow a similar distribution. More specifically, we randomly assign 80% of the observations to the training set, which we use to estimate the learnable parameter set, Θ. 10% of the observations are reserved for the validation set, which we use to fine-tune the hyperparameters of the operators. We use the remaining 10% of the sample as the test set, which we use to measure the predictive performance of each machine learning technique. Specifically, we focus on metrics, such as out-of-sample R-squared (R^2_{POS}), mean absolute prediction error (MAPE), and root mean squared prediction error (RMSPT). For consistency across models and regularization approaches, all industry characteristics are normalized to have zero mean and standard deviation of one.

We take a grid search approach to choose the hyperparameters that result in the best-performing technique in the validation set. That is, for each hyperparameter we consider a target value set, e.g., $\lambda_{ML} \in \{0.01, 0.1, 1, 10, 100\}$ and train the models separately using each of these values and the observations of the training set. Then based on the in-sample R^2 metric of the models for the observations in the validation set, we choose the hyperparameter with the best performance. Below we summarize our choices for the key hyperparameters, Λ_{ML}.

- Linear Models

We include an intercept in all linear regression estimators. Other than this, there is no hyperparameter for the ordinary least squares method. For the LASSO estimator, we choose the regularization parameter, $\lambda_{ML} = 0.00001$, which scales the effect of L_1 penalty. For the Ridge estimator, we choose the regularization parameter, $\lambda_{ML} = 10$, which scales the effect of L_2 penalty. For the ElasticNet estimator, we choose the regularization parameter, $\lambda_{ML} = 0.00001$ and the ElasticNet mixing parameter, $l1_{ratiofloat} = 0.5$ to allow for a combination of L_1 and L_2 penalties. Choosing $l1_{ratiofloat} = 0$ is equivalent of using the Ridge operator while choosing $l1_{ratiofloat} = 1$ converts the Elastic net operator to a LASSO estimator. Note that setting the regularization parameter $\lambda_{ML} = 0$ in LASSO, Ridge, or Elastic net regressions converts these estimators to the ordinary least square operator. Lastly, we choose to keep 30 and 5 components for the PCA and PLS estimators, respectively.

- Tree-based Models

For the RFR estimator, we choose to have 100 trees in the forest, each with a maximum depth of 10. In each tree, we require at least two samples to split an internal node and at least one sample at a leaf node (end node). By relaxing these two constraints, we shape the trees using the maximum depth attribute. For the GBRT estimator, we choose a learning rate of 0.1, and we perform 100 boosting stages on trees with a maximum depth of 5. Note that there is a trade-off between the two and our choice of the learning rate shrinks the contribution of each tree by 10% while the 100 boosting stage provides a sufficiently high performance. In each tree, we require at least two samples to split an internal node and at least one sample at a leaf node (end node). Lastly, for the XGBoost estimator, we choose a learning rate of 0.3 and trees with a maximum depth of 10. We also choose the 0 and 1 weights for the L_1 and L_2 regularization terms, respectively.

- Neural Networks

For the multi-layer Perceptron (MLP) implementation of the feed-forward neural networks, we choose to have 100 hidden layers with a strength of the L_2 regularization term equal to 0.001.

E Additional Figures and Tables

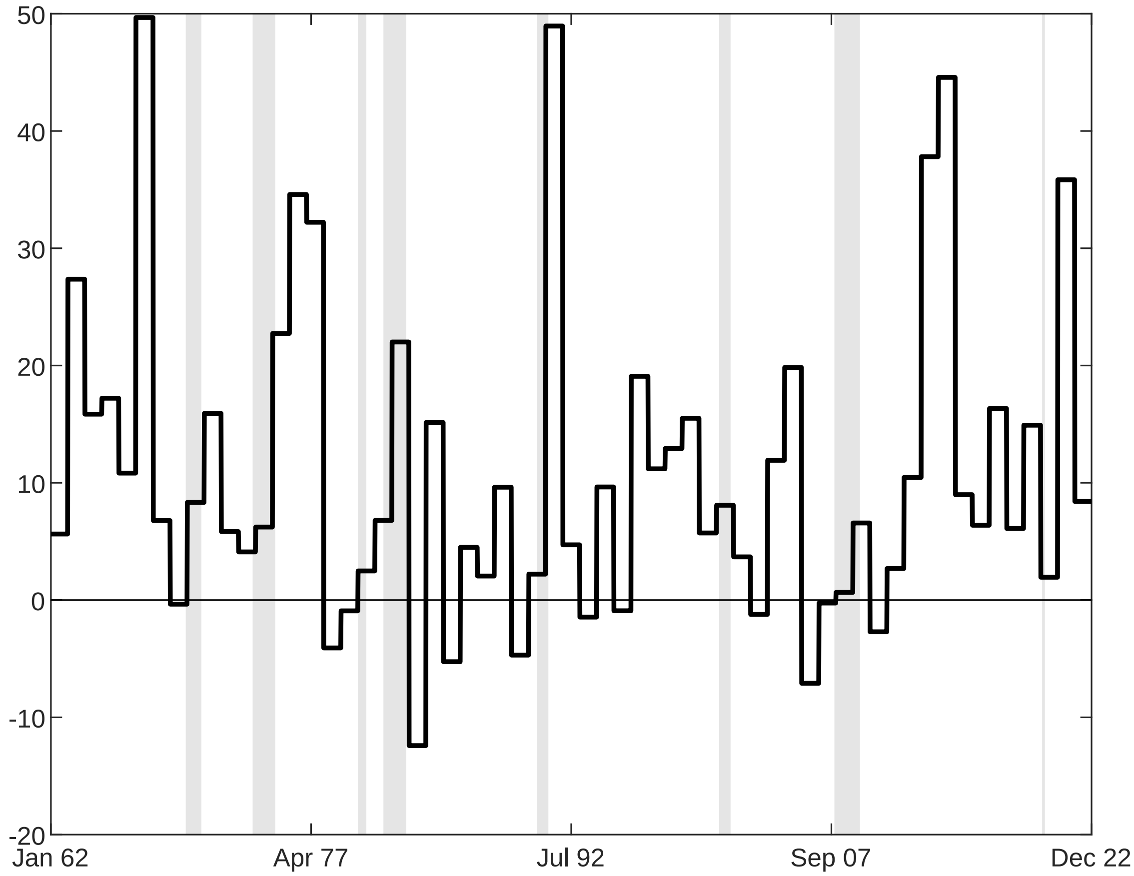


Figure A1. The figure shows the price of market risk estimated from a a specification of the ICAPM which assumes that $\gamma_j = 0, \ \forall \ j$, considering a constant price over each calendar year. The shaded areas depict the NBER recession periods. The sample period is from start of January 1962 to end of December 2022 at the weekly frequency. The sample does not include the following six industries due to missing observations from 1962 to 1985: Candy & Soda, Computer Software, Defense, Fabricated Products, Healthcare, and Precious Metals.

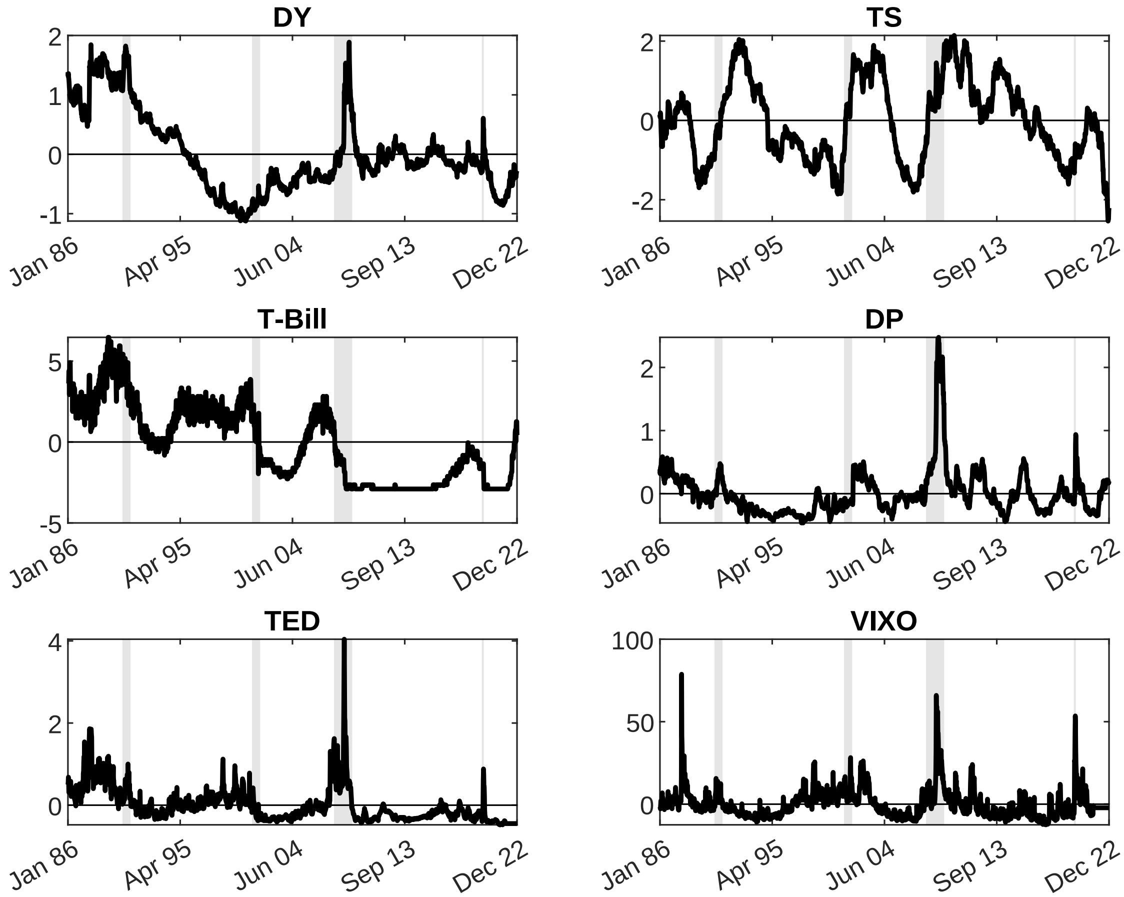


Figure A2. The figure plots the time-series of the demeaned information variables, used for conditional asset pricing tests. It shows the US market dividend yield (DY), term spread (TS), the short-term interest rate (T-Bill), default premium (DP), TED spread (TED), and the VIX Index (VIXO). The shaded areas depict the NBER recession periods. The sample period is from January 1986 to December 2022 at the weekly frequency.

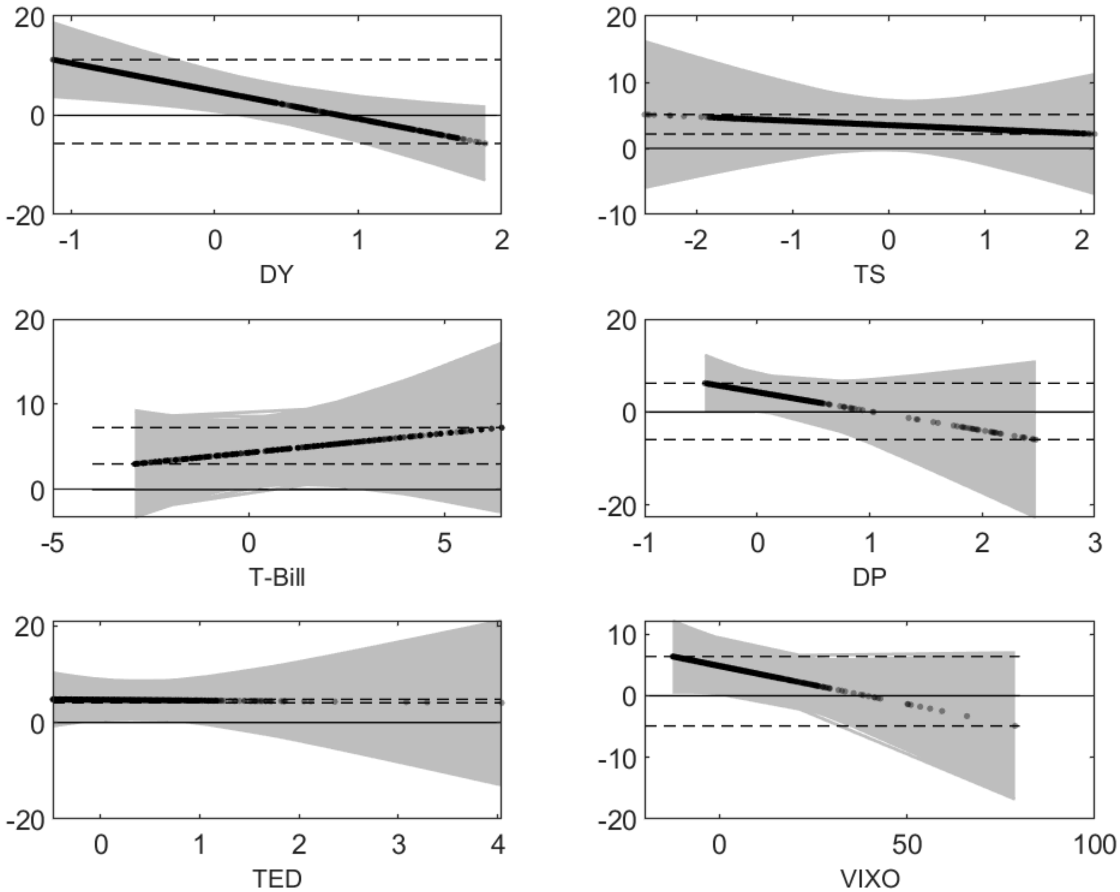


Figure A3. The figure plots the price of Bond risk, estimated from a specification of ICAPM which assumes that $\gamma_{\Delta \text{Bond}} \neq 0$, conditional on one information variable. The Bond risk is estimated from the covariation of asset returns with the returns of the 10-year maturity Treasury bond. Each panel represents the results using the lagged and demeaned values of the US market dividend yield (DY), term spread (TS), the short-term interest rate (T-Bill), Default Premium (DP), TED spread (TED), and the VIX Index (VIXO) as the information variable. The 95% conditional confidence intervals are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. The dotted lines show the maximum and minimum values of the estimated prices of risk. The sample period is from January 1986 to December 2022 at the weekly frequency.

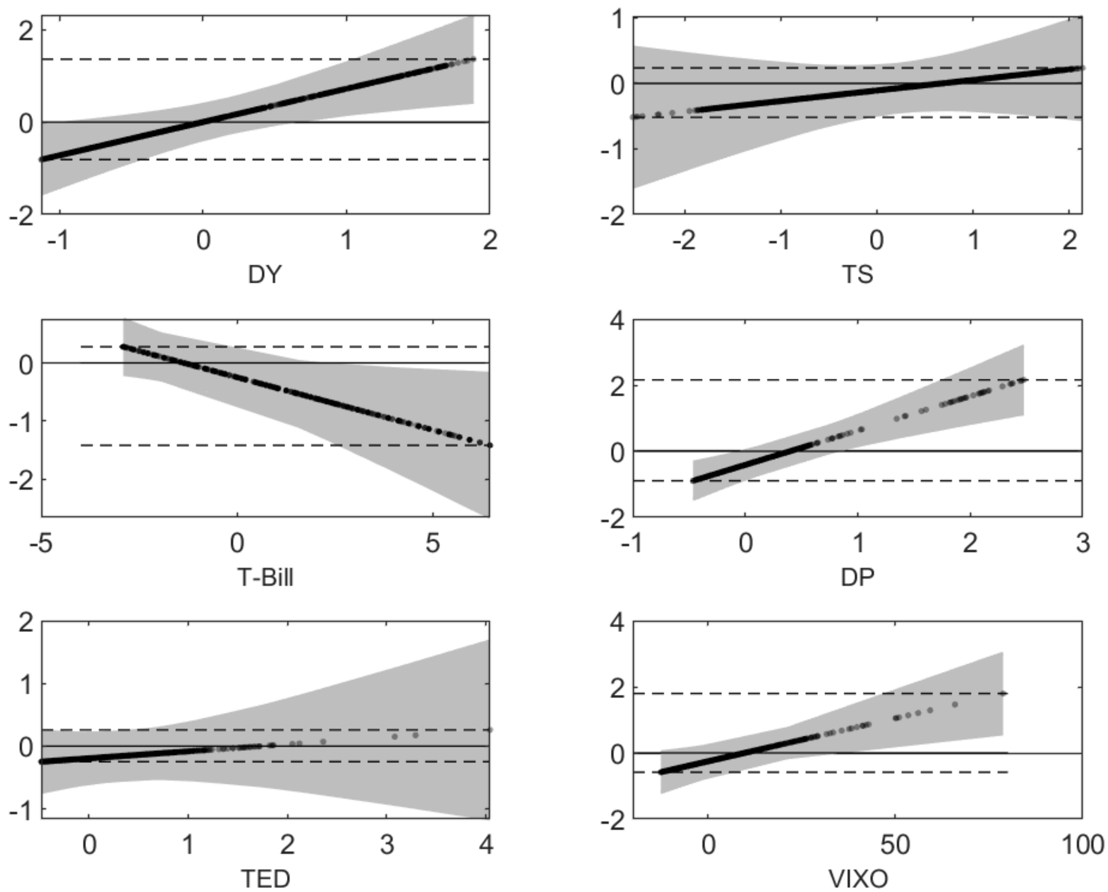


Figure A4. The figure plots the price of Term Spread risk, estimated from a specification of ICAPM which assumes that $\gamma_{\Delta \text{TS}} \neq 0$, conditional on one information variable. The Term Spread risk is estimated from the covariation of asset returns with the innovations in the Term Spread. Each panel represents the results using the lagged and demeaned values of the US market dividend yield (DY), term spread (TS), the short-term interest rate (T-Bill), Default Premium (DP), TED spread (TED), and the VIX Index (VIXO) as the information variable. The 95% conditional confidence intervals are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. The dotted lines show the maximum and minimum values of the estimated prices of risk. The sample period is from January 1986 to December 2022 at the weekly frequency.

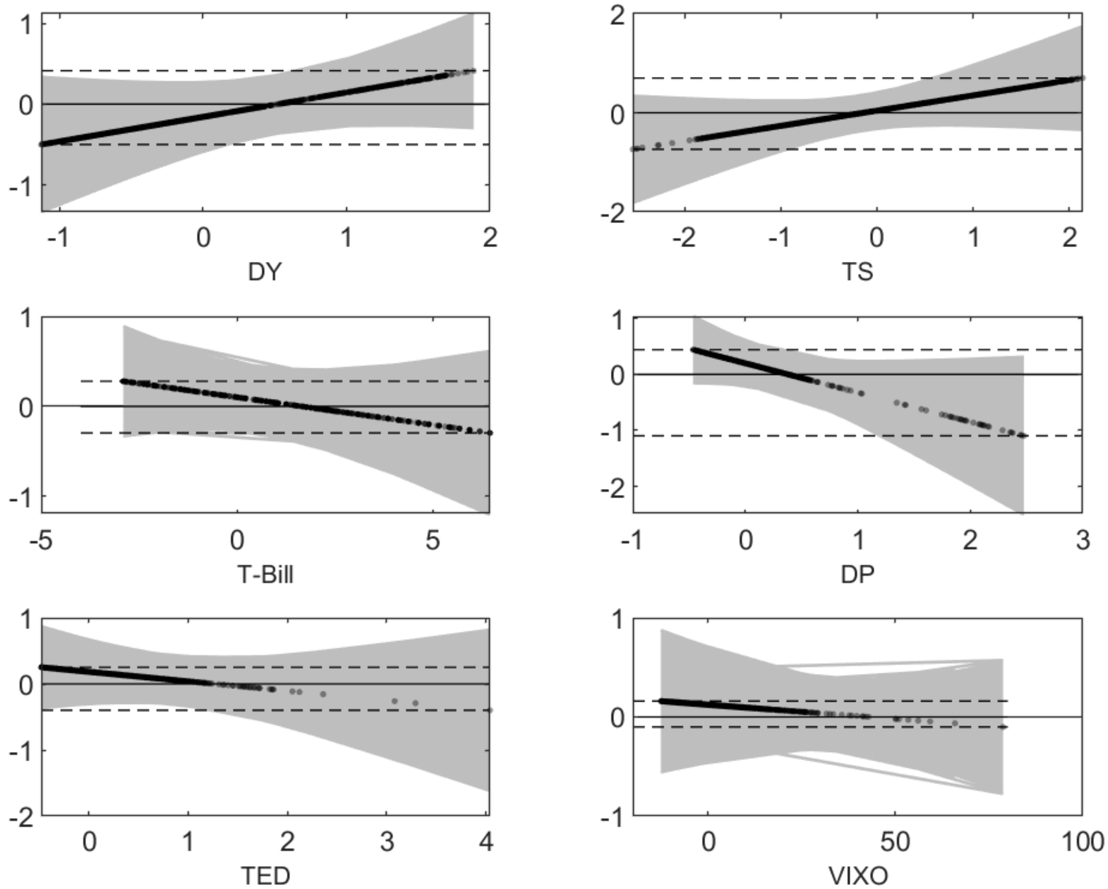


Figure A5. The figure plots the price of Effective Federal Fund Rate risk, estimated from a specification of ICAPM which assumes that $\gamma_{\Delta \text{EFFR}} \neq 0$, conditional on one information variable. The Effective Federal Fund Rate risk is estimated from the covariation of asset returns with the innovations in the Federal Fund Rate. Each panel represents the results using the lagged and demeaned values of the US market dividend yield (DY), term spread (TS), the short-term interest rate (T-Bill), Default Premium (DP), TED spread (TED), and the VIX Index (VIXO) as the information variable. The 95% conditional confidence intervals are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. The dotted lines show the maximum and minimum values of the estimated prices of risk. The sample period is from January 1986 to December 2022 at the weekly frequency.

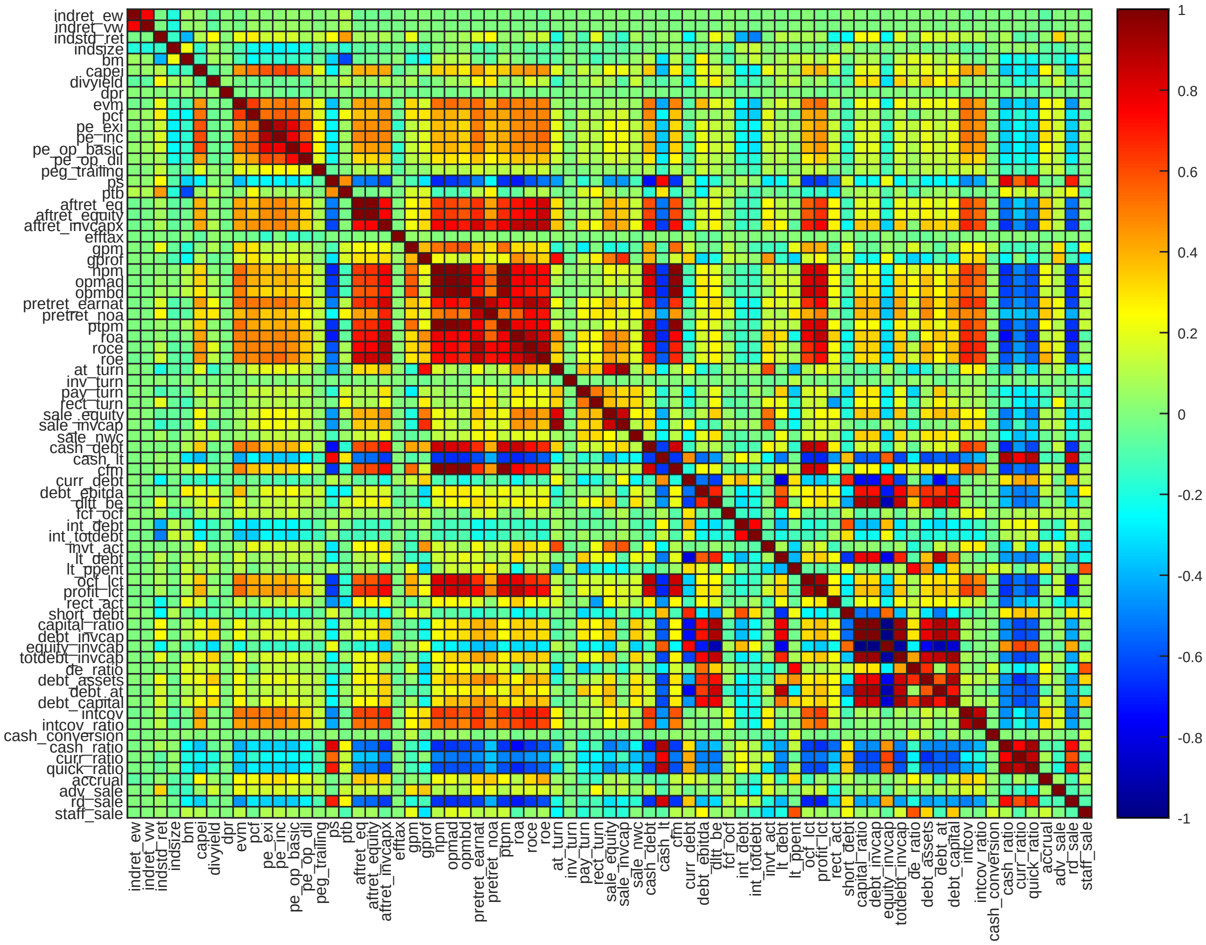


Figure A6. The figure plots the heatmap diagram for the cross-correlations between firm characteristics.

Table A1. This table introduces the industry groupings.

Industry Name	Abv.	Group	Industry Name	Abv.	Group
Aircraft	Aero	Sensitive	Insurance	Insur	Cyclical
Agriculture	Agric	Defensive	Measuring and Control Equipment	LabEq	Sensitive
Automobiles and Trucks	Autos	Cyclical	Machinery	Mach	Sensitive
Banking	Banks	Cyclical	Restaurants, Hotels, Motels	Meals	Cyclical
Beer & Liquor	Beer	Defensive	Medical Equipment	MedEq	Defensive
Construction Materials	BldMt	Cyclical	Non-Metallic and Industrial Metal Mining	Mines	Sensitive
Printing and Publishing	Books	Sensitive	Petroleum and Natural Gas	Oil	Sensitive
Shipping Containers	Boxes	Sensitive	Almost Nothing	Others	Others
Business Services	BusSv	Others	Business Supplies	Paper	Sensitive
Chemicals	Chems	Cyclical	Personal Services	PerSv	Others
Electronic Equipment	Chips	Sensitive	Real Estate	RlEst	Cyclical
Apparel	Clths	Cyclical	Retail	Rtail	Cyclical
Construction	Cnstr	Cyclical	Rubber and Plastic Products	Rubbr	Cyclical
Coal	Coal	Sensitive	Shipbuilding, Railroad Equipment	Ships	Sensitive
Pharmaceutical Products	Drugs	Defensive	Tobacco Products	Smoke	Defensive
Electrical Equipment	ElcEq	Sensitive	Candy & Soda	Soda	Defensive
Fabricated Products	FabPr	Sensitive	Computer Software	Softw	Sensitive
Trading	Fin	Cyclical	Steel Works Etc	Steel	Sensitive
Food Products	Food	Defensive	Communication	Telcm	Sensitive
Entertainment	Fun	Cyclical	Recreation	Toys	Cyclical
Precious Metals	Gold	Defensive	Transportation	Trans	Sensitive
Defense	Guns	Sensitive	Textiles	Txtls	Cyclical
Computers	Hardw	Sensitive	Utilities	Util	Defensive
Healthcare	Hlth	Defensive	Wholesale	Whlsl	Others
Consumer Goods	Hshld	Sensitive			

Table A2. This table introduces the industry characteristics.

Category	Characteristic Name	Abv.	Description
Return	Stock Return (ew)	indret_ew	Equal weighted monthly stock returns of firms in an industry
Return	Stock Return (vw)	indret_vw	Value weighted monthly stock returns of firms in an industry
Return	Stock Risk	indstd_ret	Standard deviation of daily value-weighted industry returns in a month
Return	Stock Size	indsize	Log of the average firm size per industry
Valuation	Book/Market	bm	Book Value of Equity as a fraction of Market Value of Equity
Valuation	Dividend Payout Ratio	dpr	Dividends as a fraction of Income Before Extra. Items
Valuation	Dividend Yield	divyield	Indicated Dividend Rate as a fraction of Price
Valuation	Enterprise Value Multiple	evm	Multiple of Enterprise Value to EBITDA
Valuation	P/E (Diluted, Excl. EI)	pe_exi	Price-to-Earnings, excl. Extraordinary Items (diluted)
Valuation	P/E (Diluted, Incl. EI)	pe_inc	Price-to-Earnings, incl. Extraordinary Items (diluted)
Valuation	Price/Book	ptb	Multiple of Market Value of Equity to Book Value of Equity
Valuation	Price/Cash flow	pcf	Multiple of Market Value of Equity to Net Cash Flow from Operating Activities
Valuation	Price/Operating Earnings (Basic, Excl. EI)	pe_op_basic	Price to Operating EPS, excl. Extraordinary Items (Basic)
Valuation	Price/Operating Earnings (Diluted, Excl. EI)	pe_op_dil	Price to Operating EPS, excl. Extraordinary Items (Diluted)
Valuation	Price/Sales	ps	Multiple of Market Value of Equity to Sales
Valuation	Shillers Cyclically Adjusted P/E Ratio	capei	Multiple of Market Value of Equity to 5-year moving average of Net Income
Valuation	Trailing P/E to Growth (PEG) ratio	peg_trailing	Price-to-Earnings, excl. Extraordinary Items (diluted) to 3-Year past EPS Growth
Profitability	After-tax Return on Average Common Equity	aftret_eq	Net Income as a fraction of the average of Common Equity based on most recent two periods
Profitability	After-tax Return on Invested Capital	aftret_invcapx	Net Income plus Interest Expenses as a fraction of Invested Capital
Profitability	After-tax Return on Total Stockholders' Equity	aftret_equity	Net Income as a fraction of average of Total Shareholders' Equity based on most recent two periods
Profitability	Effective Tax Rate	efftax	Income Tax as a fraction of Pretax Income
Profitability	Gross Profit Margin	gpm	Gross Profit as a fraction of Sales
Profitability	Gross Profit/Total Assets	gprof	Gross Profitability as a fraction of Total Assets
Profitability	Net Profit Margin	npm	Net Income as a fraction of Sales
Profitability	Operating Profit Margin After Depreciation	opmad	Operating Income After Depreciation as a fraction of Sales
Profitability	Operating Profit Margin Before Depreciation	opmbd	Operating Income Before Depreciation as a fraction of Sales
Profitability	Pre-tax Profit Margin	ptpm	Pretax Income as a fraction of Sales
Profitability	Pre-tax return on Net Operating Assets	pretret_noa	Operating Income After Depreciation as a fraction of average Net Operating Assets (NOA) based on most recent two periods, where NOA is defined as the sum of Property Plant and Equipment and Current Assets minus Current Liabilities
Profitability	Pre-tax Return on Total Earning Assets	pretret_earnat	Operating Income After Depreciation as a fraction of average Total Earnings Assets (TEA) based on most recent two periods, where TEA is defined as the sum of Property Plant and Equipment and Current Assets

Table continues ...

Table A2 continues,

Category	Characteristic Name	Abv.	Description
Profitability	Return on Assets	roa	Operating Income Before Depreciation as a fraction of the average Total Assets based on most recent two periods
Profitability	Return on Capital Employed	roce	Earnings Before Interest and Taxes as a fraction of average Capital Employed based on most recent two periods, where Capital Employed is the sum of Debt in Long-term and Current Liabilities and Common/Ordinary Equity
Profitability	Return on Equity	roe	Net Income as a fraction of average Book Equity based on most recent two periods, where Book Equity is defined as the sum of Total Parent Stockholders' Equity and Deferred Taxes and Investment Tax Credit
Efficiency	Asset Turnover	at_turn	Sales as a fraction of the average Total Assets based on the most recent two periods
Efficiency	Inventory Turnover	inv_turn	COGS as a fraction of the average Inventories based on the most recent two periods
Efficiency	Payables Turnover	pay_turn	COGS and change in Inventories as a fraction of the average of Accounts Payable based on the most recent two periods
Efficiency	Receivables Turnover	rect_turn	Sales as a fraction of the average of Accounts Receivables based on the most recent two periods
Efficiency	Sales/Invested Capital	sale_invcap	Sales per dollar of Invested Capital
Efficiency	Sales/Stockholders Equity	sale_equity	Sales per dollar of total Stockholders' Equity
Efficiency	Sales/Working Capital	sale_nwc	Sales per dollar of Working Capital, defined as the difference between Current Assets and Current Liabilities
Financial Soundness	Cash Balance/Total Liabilities	cash_lt	Cash Balance as a fraction of Total Liabilities
Financial Soundness	Cash Flow Margin	cfm	Income before Extraordinary Items and Depreciation as a fraction of Sales
Financial Soundness	Cash Flow/Total Debt	cash_debt	Operating Cash Flow as a fraction of Total Debt
Financial Soundness	Current Liabilities/Total Liabilities	curr_debt	Current Liabilities as a fraction of Total Liabilities
Financial Soundness	Free Cash Flow/Operating Cash Flow	fcf_ocf	Free Cash Flow as a fraction of Operating Cash Flow, where Free Cash Flow is defined as the difference between Operating Cash Flow and Capital Expenditures
Financial Soundness	Interest/Average Long-term Debt	int_debt	Interest as a fraction of average Long-term debt based on most recent two periods
Financial Soundness	Interest/Average Total Debt	int_totdebt	Interest as a fraction of average Total Debt based on most recent two periods
Financial Soundness	Inventory/Current Assets	invt_act	Inventories as a fraction of Current Assets
Financial Soundness	Long-term Debt/Book Equity	dltt_be	Long-term Debt to Book Equity
Financial Soundness	Long-term Debt/Total Liabilities	lt_debt	Long-term Debt as a fraction of Total Liabilities
Financial Soundness	Operating CF/Current Liabilities	ocf_lct	Operating Cash Flow as a fraction of Current Liabilities

Table continues ...

Table A2 continues,

Category	Characteristic Name	Abv.	Description
Financial Soundness	Receivables/Current Assets	rect_act	Accounts Receivables as a fraction of Current Assets
Financial Soundness	Short-Term Debt/Total Debt	short_debt	Short-term Debt as a fraction of Total Debt
Financial Soundness	Total Debt/EBITDA	debt_ebitda	Gross Debt as a fraction of EBITDA
Financial Soundness	Total Liabilities/Total Tangible Assets	lt_ppent	Total Liabilities to Total Tangible Assets
Capitalization	Capitalization Ratio	capital_ratio	Total Long-term Debt as a fraction of the sum of Total Long-term Debt, Common/Ordinary Equity and Preferred Stock
Capitalization	Common Equity/Invested Capital	equity_invcap	Common Equity as a fraction of Invested Capital
Capitalization	Long-term Debt/Invested Capital	debt_invcap	Long-term Debt as a fraction of Invested Capital
Capitalization	Total Debt/Invested Capital	totdebt_invcap	Total Debt (Long-term and Current) as a fraction of Invested Capital
Solvency	After-tax Interest Coverage	intcov	Multiple of After-tax Income to Interest and Related Expenses
Solvency	Interest Coverage Ratio	intcov_ratio	Multiple of Earnings Before Interest and Taxes to Interest and Related Expenses
Solvency	Total Debt/Capital	debt_capital	Total Debt as a fraction of Total Capital, where Total Debt is defined as the sum of Accounts Payable and Total Debt in Current and Long- term Liabilities, and Total Capital is defined as the sum of Total Debt and Total Equity (common and preferred)
Solvency	Total Debt/Equity	de_ratio	Total Liabilities to Shareholders' Equity (common and preferred)
Solvency	Total Debt/Total Assets	debt_assets	Total Debt as a fraction of Total Assets
Solvency	Total Debt/Total Assets	debt_at	Total Liabilities as a fraction of Total Assets
Liquidity	Cash Conversion Cycle (Days)	cash_conversion	Inventories per daily COGS plus Account Receivables per daily Sales minus Account Payables per daily COGS
Liquidity	Cash Ratio	cash_ratio	Cash and Short-term Investments as a fraction of Current Liabilities
Liquidity	Current Ratio	curr_ratio	Current Assets as a fraction of Current Liabilities
Liquidity	Quick Ratio (Acid Test)	quick_ratio	Quick Ratio: Current Assets net of Inventories as a fraction of Current Liabilities
Other	Accruals/Average Assets	accrual	Accruals as a fraction of average Total Assets based on most recent two periods
Other	Avertising Expenses/Sales	adv_sale	Advertising Expenses as a fraction of Sales
Other	Labor Expenses/Sales	staff_sale	Labor Expenses as a fraction of Sales
Other	Research and Development/Sales	rd_sale	R&D expenses as a fraction of Sales

Table A3. The table presents the aggregated values of firm characteristics through time, averaged over the cross-section of industries. Column $\overline{\text{ALL}}$ presents the mean of these values over the sample period, whereas column $\overline{\text{Rec.}} - \overline{\text{Exp.}}$ reports the difference in their mean values during the NBER expansion and recession periods. Column Chr.:Rec. reports the slope coefficients from regressions of characteristic values on a time trend interacted with an NBER recession dummy. The sample period is from January 1986 to December 2022 at the weekly frequency.

Characteristic	$\overline{\text{ALL}}$	$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	Chr.:Rec.	Characteristic	$\overline{\text{ALL}}$	$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	Chr.:Rec.
indret_ew	0.011	-0.030	1.035***	sale_invcap	1.427	0.037	0.412***
indret_vw	0.010	-0.030	0.639***	sale_nwc	6.056	0.044	4.565***
indsize	7.486	-0.148	-6.877***	cash_debt	0.106	0.008	0.071***
indstd_ret	1.320	1.077	19.246***	cash_lt	0.226	-0.017	-0.448***
bm	0.579	0.102	4.122***	cfm	0.066	0.000	-0.249***
capei	13.967	-2.811	-88.940***	curr_debt	0.490	0.014	-0.075***
divyield	0.021	0.005	0.127***	debt_ebitda	1.629	-0.052	0.962***
dpr	0.140	-0.027	0.171***	dltt_be	0.414	-0.002	0.200***
evm	8.185	-0.451	-27.139***	fcf_ocf	0.458	0.005	-0.245
pcf	7.221	-1.528	-48.518***	int_debt	0.095	0.008	-0.102***
pe_exi	11.085	-2.611	-97.647***	int_totdebt	0.073	0.008	-0.101***
pe_inc	10.708	-2.899	-75.775***	invt_act	0.240	0.000	0.112***
pe_op_basic	11.172	-2.454	-82.076***	lt_debt	0.326	-0.013	0.031
pe_op_dil	15.889	-3.655	-86.330***	lt_ppent	5.103	-0.141	0.498
peg_trailing	0.519	-0.131	-4.454***	ocf_lct	0.320	0.006	-0.010
ps	1.405	-0.372	-8.939***	profit_lct	0.483	-0.001	-0.731***
ptb	2.047	-0.452	-10.460***	rect_act	0.335	0.009	-0.070***
aftret_eq	0.071	-0.006	-0.395***	short_debt	0.174	0.012	0.017
aftret_equity	0.068	-0.007	-0.383***	capital_ratio	0.282	-0.003	0.143***
aftret_invcapx	0.062	-0.003	-0.332***	debt_invcap	0.282	-0.005	0.130***
efftax	0.272	0.065	0.091***	equity_invcap	0.697	0.004	-0.128***
gpm	0.328	0.000	-0.064***	totdebt_invcap	0.374	0.004	0.184***
gprof	0.284	0.004	-0.014	de_ratio	1.418	0.068	0.501**
npm	0.012	0.001	-0.273***	debt_assets	0.543	0.004	0.096***
opmad	0.057	0.004	-0.143***	debt_at	0.237	-0.002	0.120***
opmbd	0.108	0.003	-0.135***	debt_capital	0.431	-0.001	0.135***
pretret_earnat	0.093	0.000	-0.140***	intcov	2.550	-0.409	-11.848***
pretret_noa	0.152	-0.005	-0.116***	intcov_ratio	3.622	-0.517	-3.207***
ptpm	0.029	0.002	-0.376***	cash_conversion	167.170	-76.249	67.102***
roa	0.099	0.001	-0.136***	cash_ratio	0.542	-0.050	-1.234***
roce	0.092	-0.003	-0.187***	curr_ratio	2.015	-0.065	-1.350***
roe	0.066	-0.005	-0.493***	quick_ratio	1.434	-0.055	-1.290***
at_turn	0.950	0.015	-0.086	accrual	-0.045	-0.007	-0.187***
inv_turn	29.200	-17.203	-23.036***	adv_sale	0.005	0.000	-0.002
pay_turn	9.557	-0.038	6.071***	rd_sale	0.021	0.004	-0.029***
rect_turn	9.262	-0.082	1.425	staff_sale	0.012	-0.003	0.006
sale_equity	2.209	0.084	1.122***				

Table A4. This table presents the average (Mean) and standard deviation (St. Dev.) of conditional covariances of industry excess returns with market risk, as well as the proxies for the intertemporal risk, including the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR). Panel A presents these statistics averaged over all industries and time ($\overline{\text{ALL}}$). It also reports the difference in these values during the NBER recession and expansion periods ($\overline{\text{Rec.}} - \overline{\text{Exp.}}$). Panel B presents these statistics for each industry over time. Conditional covariances are from weekly returns (in percentage) and are calculated through the Asymmetric Dynamic Conditional Correlation (ADCC) methodology. The sample period is from January 1986 to December 2022 at the weekly frequency.

	$Cov_t(R_i, \text{Market})$		$Cov_t(R_i, \text{Bond})$		$Cov_t(R_i, \Delta\text{TS})$		$Cov_t(R_i, \Delta\text{DP})$		$Cov_t(R_i, \Delta\text{EFFR})$	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Panel A: Business Cycle										
$\overline{\text{ALL}}$	0.055	0.083	-0.294	0.766	0.805	7.131	-1.586	4.327	-1.334	5.014
$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	0.103	0.148	-0.473	0.513	-6.610	3.037	-4.667	9.935	-0.139	8.206
Panel B: Industry										
Aero	6.045	9.826	-0.402	0.818	0.805	10.197	-1.462	4.581	-0.742	4.195
Agric	4.259	5.556	-0.307	0.520	0.102	4.378	-1.640	2.828	-1.950	4.737
Autos	7.070	10.252	-0.535	0.828	2.241	9.140	-2.703	8.459	-1.043	3.017
Banks	6.580	9.587	-0.376	1.211	1.945	10.002	-1.326	3.547	-2.278	7.703
Beer	3.582	4.976	0.159	0.442	-1.635	5.277	-0.724	1.474	-1.104	1.902
BldMt	6.312	10.193	-0.326	0.815	1.303	7.479	-2.149	6.542	-1.498	3.459
Books	5.815	8.970	-0.247	0.800	0.674	7.876	-1.873	6.623	-2.220	7.604
Boxes	5.357	7.386	-0.295	0.577	1.434	5.759	-1.250	2.551	-1.534	2.316
BusSv	6.273	10.032	-0.291	0.779	0.453	8.064	-1.547	4.690	-1.524	6.408
Chems	5.840	8.602	-0.512	0.806	2.169	8.123	-2.100	5.017	-1.611	2.223
Chips	7.331	8.806	-0.480	0.741	1.367	7.369	-1.972	2.861	-2.607	6.330
Clths	5.944	8.247	-0.341	0.625	1.548	6.094	-1.025	2.724	-1.855	2.592
Cnstr	6.869	10.311	-0.298	0.852	-0.155	7.636	-1.756	4.186	-2.454	4.322
Coal	6.186	8.597	-0.730	0.920	4.416	8.170	-1.793	4.536	-3.906	13.666
Drugs	4.420	5.695	0.068	0.488	-1.341	4.415	-0.736	1.288	-1.465	1.743
ElcEq	6.836	8.645	-0.371	0.898	1.192	7.538	-1.664	5.165	-2.580	4.877
FabPr	6.168	8.634	-0.583	0.727	2.021	7.030	-3.141	9.309	-0.306	2.154
Fin	7.327	10.148	-0.478	1.086	2.021	12.001	-1.741	4.458	-2.013	7.472
Food	3.311	4.672	0.104	0.520	-1.014	4.669	-0.463	1.200	-1.132	1.915
Fun	7.034	11.324	-0.331	0.886	-0.293	7.031	-2.292	4.703	-0.961	2.759
Gold	1.470	2.607	-0.086	0.834	1.023	4.811	-1.959	2.749	-0.842	5.168
Guns	3.560	5.315	-0.029	0.325	0.177	4.265	-0.776	1.303	0.753	0.980

Table continues ...

Table A4 continues

	$Cov_t(R_i, \text{Market})$		$Cov_t(R_i, \text{Bond})$		$Cov_t(R_i, \Delta\text{TS})$		$Cov_t(R_i, \Delta\text{DP})$		$Cov_t(R_i, \Delta\text{EFFR})$	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Hardw	6.686	7.309	-0.474	0.578	1.138	5.589	-1.344	2.115	-1.282	2.986
Hlth	4.906	7.753	-0.160	0.404	-0.228	4.479	-1.421	3.038	-0.728	5.185
Hshld	3.941	5.966	0.051	0.506	-1.137	5.201	-0.733	1.813	-1.302	4.438
Insur	5.646	10.464	-0.173	0.820	0.120	8.885	-1.313	3.280	-1.238	2.200
LabEq	6.485	8.574	-0.405	0.671	0.973	7.827	-1.995	4.324	-1.653	6.986
Mach	7.070	10.342	-0.650	0.870	3.337	7.858	-2.219	6.532	-1.429	6.036
Meals	4.822	6.809	-0.112	0.602	-0.255	4.925	-1.188	2.186	-1.194	1.972
MedEq	5.111	7.540	-0.071	0.513	-0.724	5.320	-1.066	2.362	-1.326	1.925
Mines	6.011	9.373	-0.752	0.749	4.007	6.628	-2.559	4.612	-1.511	2.434
Oil	4.950	7.964	-0.445	0.764	2.341	7.413	-1.733	5.065	0.319	4.050
Other	5.127	5.783	-0.274	0.651	0.431	6.579	-1.260	2.388	-1.642	2.152
Paper	4.901	6.166	-0.332	0.589	0.903	7.325	-1.629	2.496	-1.346	2.111
PerSv	5.569	8.301	-0.172	0.720	0.163	6.073	-1.439	4.329	-0.241	8.751
RlEst	5.851	12.014	-0.425	0.895	1.059	5.704	-2.226	8.635	-1.045	4.202
Rtail	5.477	6.665	-0.167	0.564	0.470	5.547	-1.058	1.555	-2.203	5.254
Rubbr	5.489	7.761	-0.212	0.625	0.822	5.341	-1.640	2.868	-1.503	1.737
Ships	5.318	7.494	-0.519	0.757	2.512	7.301	-1.343	4.512	-1.493	6.770
Smoke	3.466	3.641	0.139	0.455	-2.253	4.083	-0.893	1.477	0.575	2.988
Soda	3.896	4.498	0.107	0.494	-1.115	3.589	-0.846	1.902	-0.195	1.552
Softw	6.849	8.244	-0.436	0.688	0.637	7.838	-1.491	1.974	-1.422	7.745
Steel	7.678	10.230	-0.953	1.072	4.505	10.969	-3.215	6.557	-0.701	5.854
Telcm	4.940	7.267	-0.099	0.770	0.394	6.016	-1.421	4.590	-0.861	1.051
Toys	5.605	6.877	-0.282	0.508	0.225	6.079	-1.799	2.979	-1.052	3.799
Trans	5.864	8.343	-0.402	0.643	1.251	6.229	-1.589	2.801	-1.709	3.751
Txtls	6.464	11.341	-0.417	0.768	1.477	8.291	-1.772	4.221	-2.610	9.062
Util	3.144	6.055	0.185	0.521	-2.484	5.272	-0.665	3.219	-0.666	2.051
Whlsl	5.500	8.889	-0.261	0.718	0.444	6.023	-1.787	4.699	-1.029	3.162

Table A5. The table reports coefficients of the asset pricing models, imposing constant prices of risk. Column 1 reports the slope coefficients for the market model, which assumes that $\gamma_j = 0$, $\forall\ j$. Columns 2 to 5 report the results for the ICAPM model with one state risk proxy, including the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR). Column 6 reports the estimates of the prices of risk for the model that includes all the macro-economic risk proxies. P-values are estimated using GLS standard errors (reported in parenthesis) corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 1986 to December 2022 at the weekly frequency.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	0.085**	0.076**	0.084**	0.077**	0.086**	0.077**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Market	2.102***	2.227***	2.081***	2.714***	2.116***	2.700***
	(0.244)	(0.255)	(0.245)	(0.269)	(0.244)	(0.271)
Bond		3.447*				
		(1.864)				
ΔTS			-0.039			-0.037
			(0.183)			(0.185)
ΔDP				1.615***		1.620***
				(0.335)		(0.337)
ΔEFFR					0.035	0.077
					(0.179)	(0.180)
Observations	94521	94521	94521	94521	94521	94521
Adjusted R^2	0.001	0.000	0.001	0.001	0.001	0.001

Table A6. The table reports the slope coefficients for the prices of risk from various ICAPM models, conditional on all information variables. Column 1 reports these values for the market model, which assumes that $\gamma_j = 0, \ \forall \ j$. Columns 2 to 5 reports them for the ICAPM models with one additional state risk proxy, such as the long-term bond return (Bond), innovations in the Term Spread (ΔTS), innovations in the Default Premium (ΔDP), and innovations in the Effective Federal Fund Rate (ΔEFFR), whereas Column 6 reports them for the ICAPM model that includes all the macro state risk proxies. The joint p-values for each price of risk are reported in Table 3. Standard errors (reported in parentheses) are estimated using GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 1986 to December 2022 at the weekly frequency.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	0.084**	0.074*	0.080**	0.087**	0.089**	0.087**
	(0.037)	(0.038)	(0.038)	(0.038)	(0.037)	(0.038)
intercept:DY	0.115	0.149*	0.124	0.100	0.127	0.123
	(0.079)	(0.080)	(0.079)	(0.079)	(0.079)	(0.080)
intercept:TS	-0.021	-0.024	-0.020	-0.022	-0.011	-0.011
	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
intercept:T-Bill	0.016	0.017	0.013	0.025	0.015	0.021
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
intercept:DP	-0.084	-0.100	-0.093	-0.043	-0.091	-0.060
	(0.149)	(0.151)	(0.149)	(0.150)	(0.149)	(0.151)
intercept:TED	-0.362***	-0.411***	-0.364***	-0.418***	-0.362***	-0.421***
	(0.126)	(0.128)	(0.126)	(0.127)	(0.126)	(0.128)
intercept:VIXO	0.008	0.009	0.009	0.007	0.007	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Market	2.130***	2.513***	1.868***	2.893***	2.222***	2.741***
	(0.492)	(0.532)	(0.512)	(0.530)	(0.497)	(0.553)
Market:DY	2.324***	1.955***	2.222***	1.272**	2.442***	1.390***
	(0.487)	(0.511)	(0.506)	(0.514)	(0.491)	(0.534)
Market:TS	-0.606*	-0.482	-0.714**	-0.570	-0.528	-0.573
	(0.324)	(0.362)	(0.331)	(0.356)	(0.328)	(0.366)
Market:T-Bill	-0.257*	-0.268*	-0.187	-0.433***	-0.286*	-0.446***
	(0.146)	(0.158)	(0.151)	(0.161)	(0.147)	(0.168)
Market:DP	-0.914*	-0.789	-0.139	-1.460**	-1.085**	-1.026
	(0.518)	(0.594)	(0.545)	(0.600)	(0.524)	(0.630)
Market:TED	-0.935***	-0.763*	-1.478***	0.607	-1.010***	0.111
	(0.362)	(0.397)	(0.400)	(0.415)	(0.366)	(0.462)
Market:VIXO	0.017	0.012	0.019	0.001	0.020	0.005
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.020)
Bond		5.762**				
		(2.408)				
Bond:DY		-14.163***				
		(3.777)				
Bond:TS		1.386				
		(2.498)				
Bond:T-Bill		0.660				
		(1.229)				

Table continues ...

Table A6 continues

	(1)	(2)	(3)	(4)	(5)	(6)
Bond:DP		3.552				
		(5.123)				
Bond :TED		10.613**				
		(4.800)				
Bond :VIXO		-0.040				
		(0.144)				
ΔTS			-0.434*			-0.403
			(0.251)			(0.256)
ΔTS:DY			0.223			0.316
			(0.401)			(0.410)
ΔTS:TS			-0.200			-0.308
			(0.236)			(0.243)
ΔTS:T-Bill			0.008			-0.039
			(0.116)			(0.119)
ΔTS:DP			1.571***			1.383***
			(0.457)			(0.472)
ΔTS:TED			-0.986***			-0.889**
			(0.382)			(0.400)
ΔTS:VIXO			-0.005			-0.002
			(0.017)			(0.018)
ΔDP				3.571***		3.726***
				(0.834)		(0.836)
ΔDP:DP				0.026		-0.515
				(0.922)		(0.931)
ΔDP:DY				-6.601***		-6.161***
				(1.051)		(1.054)
ΔDP:TS				0.533		0.667
				(0.558)		(0.559)
ΔDP:T-Bill				0.368		0.232
				(0.320)		(0.322)
ΔDP:TED				3.731***		3.825***
				(0.619)		(0.627)
ΔDP:VIXO				-0.036		-0.041
				(0.028)		(0.028)
ΔEFFR					1.106***	1.112***
					(0.388)	(0.393)
ΔEFFR:DY					0.963**	0.927**
					(0.374)	(0.380)
ΔEFFR:TS					0.920***	0.979***
					(0.347)	(0.353)
ΔEFFR:T-Bill					-0.396***	-0.387***
					(0.109)	(0.111)
ΔEFFR:DP					-1.681***	-1.217**
					(0.541)	(0.561)
ΔEFFR:TED					-0.023	-0.146
					(0.381)	(0.395)
ΔEFFR:VIXO					-0.025**	-0.023**
					(0.011)	(0.011)
Observations	94521	94521	94521	94521	94521	94521
Adjusted R^2	0.009	0.010	0.010	0.014	0.009	0.015

Table A7. The table reports the prediction performance metrics for ten machine learning techniques, adopted to predict the weekly realized returns for the industry portfolios. These metrics are the coefficient of determination over the training set (R^2_{in}) and test set (R^2_{POS}), mean absolute prediction error (MAPE), and root mean squared prediction error (RMSPE). MAPE and RMSPE values are multiplied by 100 to increase readability. We consider six linear regressions with dimension reduction, including ordinary least squares (LS), least absolute shrinkage and selection operator (LASSO), Ridge (Ridge), elastic net (ElasticNet), principal component analysis in conjunction with least squares (PCR), and partial least squares (PLS). We also consider three decision tree models, including random forest regressions (RFR), gradient-boosted regression trees (GBRT), and extreme gradient boosting (XGBoost) method. Lastly, we consider Multi-layer Perceptron (MLP) neural networks. The sample period is from January 1986 to December 2022 at the weekly frequency.

	R^2_{in}	R^2_{POS}	MAPE	RMSPE
LS	0.003	-0.008	0.029	0.042
LASSO	0.003	0.001	0.029	0.042
Ridge	0.003	-0.008	0.029	0.042
ElasticNet	0.003	-0.001	0.029	0.042
PLS.	0.002	0.000	0.029	0.042
PCR	0.002	0.001	0.029	0.042
RFR	0.027	-0.002	0.029	0.042
GBRT	0.050	-0.008	0.029	0.042
XGBOOST	0.203	-0.062	0.030	0.043
MLP	0.006	-2.674	0.032	0.080

Table A8. The table presents the aggregated SHAP values of feature contributions to the asset risk premia over time. For each feature, the average absolute SHAP values, measured based on the output of the XGBoost model, are calculated over the cross-section of all industries. Column $\overline{\text{ALL}}$ presents the mean of these values over the sample period, whereas column $\overline{\text{Rec.}} - \overline{\text{Exp.}}$ reports the difference in their means during the NBER expansion and recession periods. For the sake of better readability, weekly SHAP values are multiplied by 10,000. The sample period is from January 1986 to December 2022 at the weekly frequency.

Characteristic	$\overline{\text{ALL}}$	$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	Chr.:Rec.	Characteristic	$\overline{\text{ALL}}$	$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	Chr.:Rec.
indret_ew	0.501	0.100	0.064***	sale_invcap	2.273	2.067	0.696***
indret_vw	2.039	-0.341	-0.077***	sale_nwc	0.628	-0.137	0.023***
indsize	3.065	-0.176	-0.037	cash_debt	0.619	0.040	0.014
indstd_ret	4.628	5.645	1.592***	cash_lt	0.350	-0.026	0.006
bm	0.757	0.153	0.040***	cfm	0.337	0.049	0.003
capei	3.597	4.514	1.418***	curr_debt	1.091	-0.037	-0.010
divyield	1.991	0.022	-0.003	debt_ebitda	0.405	-0.019	-0.006
dpr	1.126	0.116	0.005	dltt_be	0.159	0.017	0.009***
evm	8.576	0.471	0.134***	fcf_ocf	0.589	-0.012	0.006
pcf	8.538	-0.567	-0.215***	int_debt	3.310	-0.877	0.051
pe_exi	0.969	-0.078	-0.087	int_totdebt	5.040	1.001	0.168***
pe_inc	0.511	-0.065	-0.010**	invt_act	0.474	0.028	0.007
pe_op_basic	2.675	-0.149	-0.079***	lt_debt	1.641	0.046	-0.023
pe_op_dil	3.190	-0.404	-0.047*	lt_ppent	0.736	-0.076	-0.005
peg_trailing	1.007	-0.092	-0.004	ocf_lct	0.332	-0.015	0.004
ps	0.454	0.065	0.018***	profit_lct	0.759	-0.030	0.005
ptb	2.821	0.411	0.126***	rect_act	1.052	-0.168	0.016
aftret_eq	0.232	-0.021	0.029***	short_debt	0.562	0.017	-0.012
aftret_equity	0.766	0.006	0.006	capital_ratio	0.190	-0.025	-0.001
aftret_invcapx	0.732	0.040	-0.004	debt_invcap	0.300	-0.003	-0.017***
efftax	3.644	-0.387	-0.107***	equity_invcap	1.077	-0.062	-0.027**
gpm	0.316	0.042	0.005	totdebt_invcap	0.196	-0.020	-0.001
gprof	0.335	0.097	0.074***	de_ratio	0.249	0.000	-0.003
npm	0.637	-0.021	-0.012	debt_assets	0.227	-0.007	0.000
opmad	0.843	-0.122	-0.021***	debt_at	0.326	-0.013	0.005
opmbd	0.239	-0.009	0.003	debt_capital	0.190	0.055	0.025***
pretret_earnat	0.110	-0.014	-0.001	intcov	0.383	0.181	0.078***
pretret_noa	0.326	0.028	0.005	intcov_ratio	2.256	-0.376	-0.088***
ptpm	0.289	0.175	0.071***	cash_conversion	2.066	0.156	0.031
roa	0.229	0.029	0.001	cash_ratio	0.358	0.048	0.008**
roce	0.170	-0.022	-0.001	curr_ratio	1.795	-0.164	-0.009
roe	0.177	0.072	0.029***	quick_ratio	0.715	0.057	0.011
at_turn	0.818	0.021	-0.014	accrual	0.722	-0.026	-0.001
inv_turn	2.215	0.201	-0.060**	adv_sale	0.094	-0.024	0.004***
pay_turn	6.515	-0.579	-0.192***	rd_sale	0.167	-0.012	0.001
rect_turn	0.708	-0.128	-0.033**	staff_sale	0.004	0.000	0.000
sale_equity	0.909	-0.061	0.025**				

Table A9. The table presents the aggregated SHAP values of feature contributions to the asset risk premia over the cross-section. For each feature, the mean absolute SHAP values, measured based on the output of the XGBoost model, are calculated over the whole time period and cross-section of industry groups: Defensive ($\overline{\text{Def.}}$), Cyclical ($\overline{\text{Cycl.}}$), Sensitive ($\overline{\text{Sens.}}$) and Others ($\overline{\text{Othr.}}$). For the sake of better readability, weekly SHAP values are multiplied by 10,000. The sample period is from January 1986 to December 2022 at the weekly frequency.

Characteristic	$\overline{\text{Def.}}$	$\overline{\text{Cycl.}}$	$\overline{\text{Sens.}}$	$\overline{\text{Othr.}}$	Characteristic	$\overline{\text{Def.}}$	$\overline{\text{Cycl.}}$	$\overline{\text{Sens.}}$	$\overline{\text{Othr.}}$
indret_ew	0.482	0.508	0.514	0.454	sale_invcap	2.103	2.239	2.333	2.525
indret_vw	2.051	2.067	2.011	2.049	sale_nwc	0.622	0.653	0.618	0.605
indsize	5.352	2.608	2.435	2.212	cash_debt	0.999	0.653	0.465	0.310
indstd_ret	5.115	4.364	4.882	3.136	cash_lt	0.403	0.376	0.323	0.252
bm	0.589	0.868	0.758	0.760	cfm	0.331	0.346	0.342	0.289
capei	3.588	3.533	3.837	2.654	curr_debt	0.951	1.076	1.166	1.125
divyield	1.775	1.987	2.104	1.986	debt_ebitda	0.467	0.463	0.332	0.395
dpr	1.002	1.177	1.079	1.480	dltt_be	0.197	0.147	0.149	0.163
evm	7.819	8.822	8.780	8.522	fcf_ocf	0.886	0.585	0.452	0.547
pcf	7.975	8.706	8.637	8.818	int_debt	3.030	3.387	3.414	3.202
pe_exi	1.213	0.688	1.097	0.772	int_totdebt	4.309	5.287	5.206	5.105
pe_inc	0.681	0.489	0.460	0.427	invt_act	0.364	0.514	0.479	0.569
pe_op_basic	2.318	2.836	2.671	2.986	lt_debt	1.484	1.650	1.704	1.680
pe_op_dil	3.026	3.261	3.091	3.833	lt_ppent	0.475	1.087	0.610	0.702
peg_trailing	1.599	0.956	0.773	0.886	ocf_lct	0.405	0.318	0.325	0.242
ps	0.501	0.442	0.439	0.459	profit_lct	1.074	0.701	0.681	0.573
ptb	2.425	2.904	2.893	3.138	rect_act	1.000	1.023	1.107	1.020
aftret_eq	0.315	0.186	0.248	0.122	short_debt	0.628	0.560	0.563	0.394
aftret_equity	0.731	0.713	0.798	0.890	capital_ratio	0.234	0.157	0.206	0.124
aftret_invcapx	0.642	0.805	0.714	0.767	debt_invcap	0.245	0.301	0.335	0.268
efftax	3.637	3.673	3.705	3.246	equity_invcap	1.227	0.901	1.161	0.948
gpm	0.317	0.336	0.291	0.363	totdebt_invcap	0.268	0.171	0.183	0.180
gprof	0.423	0.274	0.341	0.309	de_ratio	0.204	0.298	0.245	0.192
npm	0.719	0.627	0.615	0.586	debt_assets	0.270	0.203	0.225	0.218
opmad	0.773	0.895	0.836	0.865	debt_at	0.271	0.329	0.339	0.387
opmbd	0.227	0.240	0.243	0.248	debt_capital	0.222	0.180	0.189	0.150
pretret_earnat	0.120	0.112	0.108	0.088	intcov	0.318	0.411	0.405	0.329
pretret_noa	0.298	0.308	0.360	0.293	intcov_ratio	2.547	2.062	2.319	1.943
ptpm	0.323	0.268	0.301	0.231	cash_conversion	2.707	2.042	1.809	1.845
roa	0.190	0.244	0.221	0.315	cash_ratio	0.372	0.348	0.366	0.323
roce	0.172	0.168	0.172	0.167	curr_ratio	1.730	1.823	1.812	1.770
roe	0.230	0.168	0.162	0.151	quick_ratio	0.716	0.753	0.709	0.603
at_turn	0.674	0.973	0.716	1.111	accrual	0.779	0.710	0.732	0.581
inv_turn	2.104	2.412	2.036	2.647	adv_sale	0.142	0.088	0.075	0.088
pay_turn	6.755	5.884	6.825	6.737	rd_sale	0.243	0.137	0.155	0.148
rect_turn	0.986	0.639	0.631	0.654	staff_sale	0.005	0.004	0.004	0.002
sale_equity	1.144	0.790	0.904	0.803					

Table A10. The table presents the aggregated SHAP values of feature contributions to the asset risk premia over feature characteristics. First, for each industry, the average absolute SHAP values, measured based on the output of the XGBoost model, are calculated over the sample period. In the second step, the sum of these values, over each feature characteristic, is calculated and reported. For the sake of better readability, weekly SHAP values are multiplied by 10,000. The sample period is from January 1986 to December 2022 at the weekly frequency.

Industry	ΣReturn	ΣValuation	ΣProfitability	ΣEfficiency	ΣFinancial Soundness	ΣCapitalization	ΣSolvency	ΣLiquidity	ΣOther
Aero	9.137	34.609	8.511	14.338	16.721	1.606	3.875	4.463	0.986
Agric	9.856	37.490	9.285	14.161	16.530	1.910	3.176	4.762	1.140
Autos	9.622	35.882	9.381	12.154	16.180	1.407	3.499	4.682	1.005
Banks	13.998	33.718	10.463	7.372	24.526	0.929	2.897	6.277	1.043
Beer	8.039	36.955	8.301	15.351	18.129	1.845	4.669	4.890	0.949
BldMt	7.991	36.240	9.504	12.223	17.092	1.325	3.892	4.565	1.046
Books	8.956	33.755	9.250	14.821	18.519	1.554	4.603	4.566	1.105
Boxes	9.834	35.331	8.744	13.822	17.973	3.120	3.708	4.890	1.062
BusSv	6.972	35.571	9.710	14.479	17.535	1.519	3.727	4.211	0.812
Chems	7.829	36.791	9.818	13.459	18.058	1.702	4.766	4.927	1.166
Chips	9.821	38.470	9.465	14.604	16.393	2.144	3.392	4.703	0.654
Clths	8.643	35.839	7.927	16.407	15.837	1.290	4.013	5.083	0.835
Cnstr	10.363	37.405	10.180	12.816	19.362	1.649	2.820	5.277	0.838
Coal	16.338	43.811	8.899	17.676	16.894	2.422	3.408	5.682	1.149
Drugs	27.996	24.669	8.757	11.388	13.957	1.678	2.715	8.472	2.335
ElcEq	8.963	37.203	9.432	13.116	15.570	1.206	3.914	4.556	0.933
FabPr	10.157	41.685	8.269	14.734	16.670	1.749	3.661	4.292	0.869
Fin	11.233	35.834	9.277	12.689	22.354	1.194	3.778	5.528	1.059
Food	6.738	34.012	9.082	13.871	17.479	1.321	4.053	4.818	0.994
Fun	10.641	39.469	8.650	15.706	17.237	2.526	2.550	5.139	0.788
Gold	29.614	34.699	9.258	14.338	14.831	2.633	4.251	6.121	1.186
Guns	8.146	36.719	9.008	14.180	16.738	1.361	4.264	4.672	0.923
Hardw	10.904	36.188	10.594	13.567	18.289	2.233	3.718	4.126	0.872
Hlth	7.398	37.865	9.069	14.936	16.184	1.561	3.137	4.961	0.616

Table continues ...

Table A10 Continued

Industry	ΣReturn	ΣValuation	ΣProfitability	ΣEfficiency	ΣFinancial Soundness	ΣCapitalization	ΣSolvency	ΣLiquidity	ΣOther
Hshld	7.301	32.747	9.612	12.575	16.926	1.044	3.772	4.512	1.018
Insur	9.480	35.135	9.066	15.952	22.337	1.645	3.547	4.218	1.142
LabEq	8.472	36.766	8.622	15.716	15.830	2.321	3.857	4.366	0.772
Mach	8.693	37.003	9.120	13.565	16.214	1.288	3.927	4.495	0.855
Meals	7.380	37.631	7.698	15.255	17.015	1.759	3.446	4.856	0.785
MedEq	12.440	31.103	10.571	13.664	14.631	2.105	3.217	5.310	1.243
Mines	13.163	36.196	8.531	14.629	18.049	1.810	3.989	5.328	1.217
Oil	11.529	35.440	9.037	12.225	19.112	2.137	3.562	4.628	0.763
Other	8.852	37.871	8.604	15.926	16.473	2.236	2.603	4.462	0.922
Paper	7.425	35.484	9.193	12.853	17.697	1.528	3.955	4.919	1.053
PerSv	7.778	38.687	8.117	14.748	16.664	1.537	3.038	4.734	0.711
RlEst	10.469	37.432	9.007	14.821	17.031	2.183	2.562	5.251	0.782
Rtail	8.755	36.390	6.455	13.725	15.579	0.794	3.967	4.430	0.881
Rubbr	7.500	37.011	9.453	13.233	17.059	1.459	3.977	4.999	1.071
Ships	9.766	37.790	8.906	13.554	17.457	1.537	3.714	4.807	1.033
Smoke	9.951	35.457	10.155	14.900	20.499	2.356	5.102	5.711	1.149
Soda	10.538	34.381	8.955	14.760	17.845	1.819	3.315	5.486	0.996
Softw	11.230	33.594	10.194	15.203	18.185	2.555	3.836	4.661	0.912
Steel	11.014	38.143	8.931	11.992	17.522	1.464	3.630	4.189	1.058
Telcm	8.686	33.952	9.329	14.145	18.739	2.839	2.665	5.217	1.191
Toys	9.323	37.237	9.485	14.579	15.790	1.510	3.075	4.519	0.761
Trans	7.300	37.495	8.641	13.930	16.868	1.759	3.018	4.847	0.884
Txtls	9.984	38.000	8.888	13.464	17.147	1.572	3.460	4.739	0.881
Util	7.427	38.475	7.736	16.514	19.961	2.511	4.694	4.718	1.091
Whlsl	7.800	34.748	8.135	15.178	15.599	0.787	3.507	4.757	0.831

Table A11. The table presents the aggregated ranking of features based on their SHAP values for the asset risk premia. For each feature, the average absolute SHAP values, measured based on the output of the XGBoost model, is calculated over time. Then features are ranked based on their SHAP values for each industry (higher SHAP values have lower ranks). Column $\overline{\text{ALL}}$ presents the cross-sectional mean of these values over the sample period, whereas column $\overline{\text{Rec.}} - \overline{\text{Exp.}}$ reports the difference in their mean values during the NBER expansion and recession periods. The sample period is from January 1986 to December 2022 at the weekly frequency.

Characteristic	$\overline{\text{ALL}}$	$\overline{\text{Rec.}} - \overline{\text{Exp.}}$	Characteristic	$\overline{\text{ALL}}$	$\overline{\text{Rec.}} - \overline{\text{Exp.}}$
indret_ew	41.490	-4.224	sale_invcap	15.000	-7.000
indret_vw	15.714	2.306	sale_nwc	36.408	6.122
indsize	12.653	1.327	cash_debt	43.184	-4.837
indstd_ret	6.633	-5.041	cash_lt	51.327	3.429
bm	32.245	-3.653	cfm	50.878	-1.939
capei	8.816	-6.490	curr_debt	25.367	0.551
divyield	16.531	-1.082	debt_ebitda	48.980	2.857
dpr	26.224	-1.429	dltt_be	65.612	-1.918
evm	1.755	0.265	fcf_ocf	41.224	0.837
pcf	1.735	1.469	int_debt	8.776	5.531
pe_exi	31.653	5.449	int_totdebt	4.816	1.041
pe_inc	41.959	5.041	invt_act	43.571	-1.102
pe_op_basic	11.735	1.306	lt_debt	20.306	-1.082
pe_op_dil	9.469	3.163	lt_ppent	41.184	2.816
peg_trailing	29.224	1.857	ocf_lct	52.082	1.776
ps	44.796	-2.408	profit_lct	32.776	1.714
ptb	10.878	-0.449	rect_act	25.551	3.224
aftret_eq	61.714	-0.041	short_debt	40.306	-0.122
aftret_equity	31.531	0.082	capital_ratio	64.082	1.592
aftret_invcapx	32.653	-1.429	debt_invcap	54.837	0.388
efftax	7.755	2.163	equity_invcap	27.531	0.408
gpm	53.816	-2.102	totdebt_invcap	61.939	1.327
gprof	51.796	-4.612	de_ratio	58.776	0.327
npm	36.714	1.633	debt_assets	59.408	0.755
opmad	29.041	3.673	debt_at	52.388	1.694
opmbd	58.429	1.020	debt_capital	63.102	-4.224
pretret_earnat	69.449	-0.184	intcov	48.245	-7.102
pretret_noa	52.061	-0.898	intcov_ratio	14.714	3.122
ptpm	54.980	-9.816	cash_conversion	16.735	-1.714
roa	59.041	-1.694	cash_ratio	50.204	-2.245
roce	64.347	1.408	curr_ratio	18.673	0.306
roe	63.959	-5.265	quick_ratio	33.531	0.469
at_turn	34.082	-0.898	accrual	32.714	2.000
inv_turn	15.020	-0.571	adv_sale	70.306	0.592
pay_turn	4.041	2.000	rd_sale	65.082	0.388
rect_turn	36.571	6.102	staff_sale	73.000	0.000
sale_equity	27.878	2.041			

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