Term structure of recession probabilities and the cross section of asset returns

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ABSTRACT

The duration of business cycles, especially recessions, changes over time, generating time-varying investor concern about recessions. I study a new macro-factor asset pricing model that links assets' risk premiums to exposure to investor concern about future recessions, measured by the term structure of recession probabilities from professional forecasters. The innovation to the slope of the term structure is a negatively priced with an economically large and significant risk premium in a wide range of assets, consistent with how the slope predicts future long-run macroeconomic activity and labor income growth. A linear factor model, including market excess return and the innovations to the level and slope of the term structure, explains a substantial fraction of the cross-sectional variation of average returns on portfolios sorted on firm characteristics including size, book-to-market equity, and asset growth. The tracking portfolios of the model help reconcile the joint cross section of returns on equities, currencies and equity index options and have comparable pricing performance to several multi-factor benchmarks. My evidence suggests that the slope of the term structure of recession probabilities is a recession state variable (Cochrane, 2005, Chapter 9), and an economic source of risk premia on assets considered can be attributed to time-varying investor concern over future recessions that is priced.

JEL classification: E37, G12, G13, G15

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1 Introduction

A central ingredient of asset pricing is that the cross section of risk premium on different assets should be determined by their exposure to *systematic risk factors*. What are relevant systematic risk factors has long been a fundamental issue in the asset pricing literature. In the Sharpe (1964)-Lintner (1965) Capital Asset Pricing Model (CAPM), the sole systematic risk factor is return on the aggregate wealth. A paradigm that differs from the Sharpe-Lintner static CAPM is the standard consumption-based capital asset pricing model (CCAPM) (Rubinstein, 1976; Breeden, 1979), where the systematic risk factor is aggregate consumption growth. However there is much evidence that the static CAPM and CCAPM have limited empirical success, and they both face great difficulties in explaining the cross section of returns on equity portfolios sorted on size and book-to-market equity (Breeden, Gibbons, and Litzenberger, 1989; Fama and French, 1992; Lettau and Ludvigson, 2001).

When investors face a time-varying investment opportunity set, dynamic asset pricing models, such as the Intertemporal CAPM (ICAPM) of Merton (1973), demonstrate that generally systematic risk factors are not limited to return on the aggregate wealth or aggregate consumption growth, but also consist of innovations to state variables that describe the time-varying investment opportunity set. Consequently an asset's risk premium should also be affected by its covariance with innovations to the state variables. Arguably, macroeconomic variables can be mapped into state variables in dynamic asset pricing models as they are closely linked to the investment opportunity set. Empirically, announcements of macroeconomic conditions do produce pervasive effects on financial markets (e.g., Flannery and Protopapadakis, 2002; Andersen, Bollerslev, Diebold, and Vega, 2003).[1] Furthermore, the idea that macroeconomic variables serve as systematic risk factors is economically appealing because these variables provide direct linkage between risk premium and the real economy in a rather detailed way, one goal put forward by Fama (1991), and respond to the question by Campbell (1996)—"What economic forces determine the price of risk?".

A prominent macro-factor model is the seminal work by Chen, Roll, and Ross (CRR, 1986), where exposure to innovations of five macroeconomic variables, such as industrial production and the slope of the Treasury yield curve, determines expected stock returns.

[1] Beber, Brandt, and Luisi (2015) find that the common components extracted from a large cross section of macroeconomic new flows are highly correlated with financial indicators and the stock market implied volatility—the CBOE VIX index.

Shanken and Weinstein (2006) question the CRR's findings, however. They show that the CRR's results are not robust to alternative estimation procedures of factor exposure and different test portfolios. Recently, Lewellen, Nagel, and Shanken (2010) criticize the prevailing practice of evaluating asset pricing models based on how well they explain the average excess returns on the Fama and French 25 size- and book-to-market-sorted portfolios. Strikingly, these authors show that the performance of several macro-factor models deteriorates substantially when test portfolios are expanded beyond the 25 portfolios and theoretical asset pricing restrictions are imposed ex-ante. Maio and Santa-Clara (2012) examine the time series and cross-sectional consistency of several multi-factor models in the context of the Merton's ICAPM. The ICAPM prescribes that if a state variable positively forecasts future market returns (or market volatility), the innovation to it should command positive (negative) risk premium in the cross-section, and vice versa. Albeit that many multi-factor models are motivated as empirical implementations of the ICAPM, however, these authors find that only few of them meet the consistency criterion. These challenges indicate that reconciling the role of macroeconomic variables in asset pricing and identifying new sources of priced macro risk factors continue to be important issues.

There is ample evidence that the duration of business cycles, especially recessions, varies over time (Filardo, 1994; Durland and McCurdy, 1994; Filardo and Gordon, 1998). As such, investors tend to have time-varying concern over future recessions. In this paper, I propose a new macro-factor model where asset risk premia are directly linked to investors' perceived recession risks. Theoretically, recessions are important moments for asset pricing because they represent bad states associated with low economic activity, high unemployment rates, and high economic uncertainty, during which a typical household tends to have above average marginal value of wealth. Assets paying more when investors' perceived recession risks increase are deemed valuable and investors are willing to accept lower returns on them, because they provide insurance against future downside consumption or labor income risks. Therefore, shocks to investors' perceived recession risk should carry negative risk premium.

Specifically, a stylized fact of business cycles is that both total employment and employee hours are highly procyclical (Altug and Labadie, 2008). Hence, investors may lose their own jobs or business in recessions, and they would prefer assets whose cash flows are insensitive to news of future recessions to hedge their labor income risks. When investors' human capital is not entirely marketable (Mayers, 1972; Campbell, 1996; Jagannathan and Wang, 1996), this hedging demand for labor income risks can have incremental impact on asset risk premia.[2] Consequently, variables that forecast future macroeconomic conditions in general, labor income in particular, are valid candidates of state variables in dynamic models. This type of variables are named as "recession state variables" by Cochrane (2005, Chapter 9). Unlike state variables in the ICAPM, recession state variables need not forecast future market returns but should forecast future macroeconomic activity and labor market conditions.

I measure investors' perceived recession risks using the term structure of recession probabilities from the Survey of Professional Forecasters (SPF), one of the oldest economic survey in U.S. This term structure contains probability forecasts of a decline in U.S. real gross domestic product (GDP) level in the current and subsequent four quarters, made by academic and industry researchers. These survey-based forecasts are forward-looking and model-free (directly derived from investor beliefs), which distinguishes them from forecasts generated by statistical models base on historical data. SPF recession probabilities exhibit strong counter-cyclic dynamics and have incremental predictive power over common business cycle indicators for recessions dated by the National Bureau of Economic Research (NBER). I summarize the term structure as a level and slope component using principal component analysis. Intuitively, an above average level of the term structure suggests that the economy is likely in a recession, while a heightened slope indicates an increasingly perceived probability that the economy will enter into a recession in the near future. Using long-horizon predictive regressions, I find that the slope of the term structure negatively predicts macroeconomic activity and labor income growth up to 12 quarters ahead, and positively predicts future expected stock market volatility, on top of common financial indicators, such as the term spread and the default spread. Its predictive power is economically large and statistically significant. This evidence lends support to the interpretation of the slope of the term structure as a recession state variable.

I estimate the risk premium for exposure to the innovation to the slope of the term structure using cross-sectional regressions on stock returns. The innovation to the slope is negatively priced in a wide range of equity portfolios, beyond the commonly used Fama-

[2] The identification of the market portfolio is empirically difficult. In the presence of non-marketable human capital and other non-traded assets, the aggregate stock market portfolio could be a rather poor proxy for the market (Roll, 1977; Boons, 2016).

French 25 size- and book-to-market-sorted portfolios, while the innovation to the level of the term structure is not robustly negatively priced. This finding on the sign of risk premia satisfies the time series and cross-sectional consistency of multi-factor models as advocated by Lewellen et al. (2010) and Maio and Santa-Clara (2012). A linear factor model, including the market excess return and the innovations to the level and slope of the term structure, explains a substantial fraction of the cross-sectional variation of average returns on portfolios sorted on firm characteristics such as size, book-to-market equity, long term past returns, and asset growth. Stochastic discount factor (SDF) tests suggested by Cochrane (2005, Chapter 13) show that the innovation to the slope, as a risk factor in the SDF, helps price test portfolios even in the presence of risk factors in other models, such as the Fama-French three-factor model (1993) and the conditional CCAPM of Lettau and Ludvigson (2001). To address the critique on testing linear factor models raised by Lewellen et al. (2010), I consider various test portfolios, including the 25 size- and book-to-market-sorted portfolios in conjunction with the Fama-French industry portfolios. I also report generalized least square (GLS) R^2s for cross-sectional regressions, as advocated by Lewellen et al., due to the appealing interpretation of the GLS R^2 as a measure of a model's proximity to the mean-variance efficient frontier. In all cross sections, the innovation to the slope is negatively priced with significantly risk premiums and the proposed linear factor model delivers a higher GLS R^2s than other macro-factor models.

In time series regressions, small and value firms have more negative exposure on the innovation to the slope of the term structure of recession probabilities than large and growth firms, and the factor exposure almost monotonically decreases in the size and book-to-market quintile. Thus, value (small) firms are fundamentally riskier than growth (large) firms, since the former pay poorly when investors update their beliefs that the aggregate economy likely enters into a recession. This evidence is consistent with extant findings that there are asymmetric variations of risks on small and value firms across business cycles (Perez-Quiros and Timmermann, 2000; Lettau and Ludvigson, 2001; Petkova and Zhang, 2005). To shed light on the monotonic pattern of factor exposure, I run predictive regressions of future changes in operating profitability (return on total assets) on the slope of the term structure. I find that a heightened slope of the term structure is associated with a larger subsequent decline in value firms' profitability, suggesting that the monotonic pattern in beta exposure can be attributed to the higher sensitive of value firms' cash flows on business cycle risk. This finding complements former evidence that value firms are distressed (Fama and French, 1993, 1995, 1996) and have higher cash flow risks than growth firms (Campbell and Vuolteenaho, 2004; Bansal, Dittmar, and Lundblad, 2005; Campbell, Polk, and Vuolteenaho, 2010).

Ideally, asset pricing models should apply to *all* assets, however, empirical asset pricing studies often focus on particular asset classes.[3] Lettau, Maggiori, and Weber (2014) uncover that the static CAPM, in conjunction with a downside stock market factor, can jointly reconcile cross sections of average returns on equity, equity index options, currencies, and commodity and sovereign bonds, thus providing a unified risk-based explanation for these asset classes. As a comparison, these authors show that asset-specific risk factors tailored to each asset class fail to explain the cross section of returns on other asset classes. To conduct cross-sectional tests on alternative asset classes, I create factor mimicking portfolios of the level and slope of the term structure and expand the set of test assets to equity index options and currencies. The factor mimicking portfolios of the recession factor model have comparable pricing performance to the downside risk CAPM (DCAPM) of Lettau et al. (2014) in the joint cross section of equity, equity index options, and currency returns. These pieces of evidence suggest that a possible economic force of risk premia on these test assets is related to investors' hedging incentives for future recession risks.

This paper is related to the empirical literature of the ICAPM, where state variables forecast the investment opportunity set. A partial list of papers includes Campbell (1996), Chen (2002), Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Hahn and Lee (2006), Petkova (2006), Maio and Santa-Clara (2012), Maio (2013), and Boons (2016). State variables in these papers, such as the term spread and the default spread, are derived from financial market data and are motivated by their ability to predict future market returns. In contrast, state variables here are motivated by their ability to predict future macroeconomic conditions and are derived from investor beliefs about future recessions. The contribution of this paper is to show directly the importance of time-varying investor concern over recessions as a recession state variable for the cross section of expected asset

[3]Lewellen et al. (2010) suggest that test assets should be expanded beyond the size and book-to-market sorted portfolios. For instance, they suggest using bond portfolios. Notable recent exceptions along this line include Constantinides, Jackwerth, and Savov (2013), Adrian, Etula, and Muir (2014), Lettau, Maggiori, and Weber (2014), and Koijen, Lustig, and Nieuwerburgh (2015), among others. Indeed, an important agenda for empirical asset pricing research is to reconcile stochastic discount factors across different asset classes, as put forward by Cochrane in his American Finance Association presidential address (Cochrane, 2011).

returns, and sheds light on the economic source of risk premia on test assets. In addition, the macro factors proposed satisfy the time series and cross-sectional consistency criterion and are robust to the Lewellen et al.'s critique. Manski (2004) argues that it is helpful to study data on expectations rather than inferring preferences and expectations from observed choices, because the latter can be consistent with various alternatives, while the examination of expectation data helps relax assumptions about expectations and sharpens identification.

This paper also relates to the literature on the joint cross section of multiple asset classes by showing that exposure to investor recession concerns help reconcile the cross section of expected returns on currencies and equity index options. Constantinides, Jackwerth, and Savov (2013) show that the CAPM with one of several crisis-related equity risk factors, such as price jumps, can well explain the cross section of stock and equity index option returns. Adrian, Etula, and Muir (2014) propose a single factor based on major broker-dealer leverage ratios, and find that average returns on Treasury bond portfolios sorted by maturity, and on stock portfolios sorted on firm characteristics, such as size, book-to-market equity, and past returns, can be explained by differences in their exposure to shocks to the leverage factor. Koijen, Lustig, and Nieuwerburgh (2015) show that a three-factor model, including market excess return, level of the yield curve, and the Cochrane-Piazzesi factor, can jointly explain the cross section of returns on stocks, Treasury bonds, and corporate bonds better than the Fama-French three-factor model. This paper differs in the economic source of risk factors and the scope of test assets. First, the term structure of recession probabilities is forward-looking and model-free measurement of investors' perceived recession risks. Empirically, I find that the term structure contains additional information about macroeconomic activity and labor income beyond the information in the yield curve. Second, I demonstrate that the recession risk factor model helps reconcile the cross section of equity index option and currency returns, in addition to equity returns.

The remainder of the paper proceeds as follows. Section 2 describes the term structure of recession probability forecasts and the construction of the level and slope of the term structure. Section 3 presents long-horizon predictive regressions, showing that the level and especially the slope of the term structure strongly predict for macroeconomic activity, labor income growth, and stock market volatility. Section 4 presents the theoretical prediction on the pricing of perceived recession risk, empirical methodology, and cross-sectional asset pricing tests. The last section concludes.

2 Data

In this section, I describe the term structure of recession probability forecasts and then explore the information content of the term structure in forecasting future recessions dated by the NBER.

SPF Recession probabilities

The measures of perceived recession risks are recession probability forecasts from the SPF database, one of the oldest economic surveys in the United States, which summarizes macroeconomic forecasts from leading financial institutions, professional forecasting firms and academic institutions. Historically, it was conducted by the American Statistical Association in conjunction with the NBER. After the second quarter of 1990, the Federal Reserve Bank of Philadelphia took it over. The SPF recession probability forecasts are probabilities of a decline in U.S. real GDP in the current quarter and subsequent four quarters. The one quarter ahead recession probability forecast was named "The Anxious Index" by New York Times journalist David Leonhardt and is used in the asset pricing literature by David and Veronesi (2013).[4]

Formally, a quarter-t forecast of quarter-$t+i$ recession probability, $Rec_{t,i}$, can be expressed as,

$$Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1}) = Pr_t(\triangle GDP_{t+i} < 0), i \in \{0, 1, ..., 4\} \tag{1}$$

where time t is measured in quarters and GDP_{t+i} refers to the level of real GDP in quarter-$t+i$. Note that the data consist of $Rec_{t,0}$, the current quarter recession probability. The reason is that the survey is released to the public in the mid-month of each quarter, much

[4]Note that, prior to 1992Q1, the targeted quantity was U.S. real GNP. For the release dates of vintage data, see `https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-release-dates.txt?la=en`. On average there are 38 individual forecasters in the cross section. In addition to recession probabilities, SPF contains forecasts on levels and growth rates of key macroeconomic quantities and prices, such as industrial production, housing starts, and CPI. For detailed description of SPF, see Croushore (1993). Several macroeconomic forecasts in SPF have been examined in the literature. For instance, SPF inflation forecasts are shown to be superior to both term structure models and leading financial indicators in forecasting future inflation (Ang, Bekaert, and Wei, 2007).

in advance of the announcement day for the actual current quarter GDP. Because there are many individual forecasters in the cross section, in what follows, I take the cross-sectional average of individual forecasts as my proxy for investor perceived recession probabilities.

Before proceeding, I introduce a set of macroeconomic quantities and prices that are closely related to business cycles. Detailed definitions of these variables and data sources are in Appendix A. The first four macro variables are quarterly growth rates of key macroeconomic quantities, all of which are seasonally adjusted. Specifically, $\triangle \boldsymbol{IP}$ denotes the growth rate of the industrial production index. $\triangle \boldsymbol{c}$ refers to the growth rate of real per capita consumption. $\triangle \boldsymbol{GDP}$ and $\triangle \boldsymbol{l}$ are the growth rates of final revised real GDP in billions of chained 2009 dollars, and real per capita labor income, respectively. The quarter-t growth rates of these variables are formed as the natural log difference of their levels between quarter-t and quarter $t-1$. The remaining four macro variables are derived from asset prices, including the term spread (**TERM**), the default spread (**DEF**), the log dividend-price ratio on the value-weighted index of all NYSE/AMEX/NASDAQ stocks from the Center for Research in Security Prices (CRSP) ($\boldsymbol{d/p}$), and the excess return on the CRSP value-weighted index (**Mkt**). In the asset pricing literature, the first three have long been viewed as business cycle indicators that predict the financial investment opportunity set. There is much evidence that they track and predict future economic activity and risk premia of stocks and bonds (e.g., Chen, Roll and Ross, 1986; Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1988, 1989; Chen, 1991; Estrella and Hardouvelis, 1991; Estrella, 2005). Table I presents summary statistics of the five SPF recession probability forecasts and the macroeconomic variables. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters in total. Panel A reports the sample moments. The sample mean of recession probabilities ranges from 17.2% (Rec_3) to 19.24% (Rec_1). The sample mean of each recession probability is always higher than the median and the gap between the two is largest for the current quarter forecast Rec_0, indicating that Rec_0 experienced more upward spikes. Notably, the sample median of the recession probabilities, robust to the presence of outliers, increases monotonically from 9.7% (Rec_0) to 16.74% (Rec_4), that is, the average term structure of recession probabilities is upward sloping. Panel B shows time series correlations between the recession probabilities and the macro variables. As expected, all recession probabilities are negatively correlated with growth rates of GDP, consumption, and labor income, and positively associated with the default spread and the dividend-price ratio. Another interesting pattern is that a higher recession probability is associated with a downward sloping yield curve, measured by the term spread, and the magnitude of the correlation is increasing in the forecasting horizon. Figure 1 shows the time series of recession probabilities. The shaded areas are recessions dated by the NBER. Each recession probability is time-varying and exhibits strong counter-cyclic dynamics.

[**Insert Table I here**]

Predicting NBER recessions

I examine the ability of the SPF recession probability forecasts to predict future NBER recessions. I estimate a probit model of the dummy variable $D_{t+i},\ i \in \{0, 1, 2, 3\}$, taking the value of 1 if quarter $t+i$ is in an NBER recession, 0 otherwise. $Rec_{t,i}$ and $Rec_{t,i+1}$ are the key predictors. The probit model is specified as follows,

$$D_{t+i} = \begin{cases} 1, \text{quarter } t+i \text{ is in an NBER recession} \\ 0, \text{otherwise} \end{cases} \tag{2}$$

$$Pr(D_{t+i} = 1|\mathcal{F}_t) = \Phi(\beta_0 + \beta_1 Rec_{t,i} + \beta_2 Rec_{t,i+1} + \gamma X_t) \tag{3}$$

where $Pr(D_{t+i} = 1|\mathcal{F}_t)$ is the probability that quarter-$t+i$ is in an NBER recession conditional on the quarter-t information set $\mathcal{F}_t$, Φ is the cumulative distribution function of a standard normal variable, and X_t is quarter-t control variables. Following Estrella and Mishkin (1998), X_t consists of the term spread (TERM) and the excess return on the value-weighted CRSP index (Mkt).[5]

Table II reports maximum likelihood estimates of the model. The left panel reports the specifications excluding the control X_t. From each forecast horizon i, $Rec_{t,i}$ enters into the probit model with a significant and positive coefficient, that is, higher values of $Rec_{t,i}$ are uniformly associated with higher likelihoods of future NBER recessions. The forecast for the next quarter $Rec_{t,i+1}$ does not provide additional information. The economic impact

[5]Estrella and Mishkin (1998) investigate the ability of various macro variables and financial variables to forecast U.S. recessions dated by the NBER. These authors conclude that the term spread and stock market return are the most powerful leading financial indicators. Here, to make the estimated coefficients comparable, both the term spread and the CRSP index return are in percentage terms.

of $Rec_{t,i}$ is sizable. The average marginal effects of $Rec_{t,i}$ range from 0.4% to 1.47%. The Hosmer-Lemeshow goodness-of-fit test does not reject any model at the 5% significance level, suggesting that the probit models fit the sample well. As probit models are nonlinear, the R^2 in ordinary least square (OLS) regressions does not apply. Estrella and Mishkin (1998) develop a pseudo R^2 of the probit model, which takes values between 0 ("no fit") and 1 ("perfect fit") and shares a similar interpretation as OLS R^2s. The pseudo R^2s for predicting D_t and D_{t+1} are 0.53 and 0.33, respectively, indicating that the recession probability forecasts of the current quarter and the next quarter do reasonably well in forecasting NBER recessions. The right panel of the table reports estimates for the full model specification. Though including leading financial variables improves the model fitting substantially, the significance and magnitudes of the coefficients on $Rec_{t,i}$ barely change. The only exception is that $Rec_{t,3}$ is subsumed by the term spread. Overall, SPF recession probabilities are strong predictors for NBER recessions and they contain incremental information beyond the information in the yield curve and the stock market returns. In unreported analyses, I also find that SPF recession probabilities significantly predict the events of negative U.S. real GDP growth.

[**Insert Table II here**]

Principal components of recession probabilities

The correlation matrix in Panel B of Table I suggests that SPF recession probabilities do not co-move with each other perfectly over time. To separate pieces of information in the term structure and summarize its dynamics concisely, a natural way is to use principal component analysis to decompose the term structure. Figure 2(A) shows the loadings of the first two principal components on each recession probability.[6] The loadings of the first principal component (hereafter $PC1$) are all positive, despite that $PC1$ has higher weights on $Rec_{t,0}$ and $Rec_{t,1}$. The second principal component (hereafter $PC2$) captures the slope of the term structure, as $PC2$ loads positively on probabilities for remote quarters and negatively on probabilities for nearby quarters. Thus $PC1$ and $PC2$ can be interpreted as the "level" and "slope" of the term structure. Figure 2(B) shows that $PC1$ accounts for 88% of the aggregate variation of the term structure and $PC2$ accounts for an additional 9.6%. Taken

[6] I do not consider $Rec_{t,4}$ in following empirical analyses, because it has four missing observations in the early sample period.

together, $PC1$ and $PC2$ account for 98% of the total variation, therefore the dynamics of the term structure can be largely summarized by $PC1$ and $PC2$, which will be my focus in the following empirical analyses.

[**Insert Table III here**]

Table III reports summary statistics of $PC1$ and $PC2$. Panel A presents their moments over the entire sample and over NBER recessions, respectively. $PC1$ has a sample mean of 32.79 and is highly volatile, with a standard deviation of 28.94. $PC1$ is fairly persistent, with a first-order autocorrelation coefficient of 0.8. The mean of $PC2$ is 15.41, consistent with the average upward sloping term structure shown in Table I, and $PC2$ is much less volatile than $PC1$. Comparing the moments across business cycles, the average of $PC1$ is much higher in recessions than in expansions, and the difference in mean between recessions and expansions is highly significant ($t = -9.66$). The average of $PC2$ is lower in recessions than in expansions, indicating that, on average, the term structure is downward sloping during recessions, although the difference is not significant ($t = -1.46$). Figure 3 plots the time series dynamics of $PC1$ and $PC2$. As evident from the figure, $PC1$ is highly counter-cyclical, as it always peaks in recessions and declines substantially in expansions. In contrast, $PC2$ behaves very differently from $PC1$. It rises quickly during several quarters immediately prior to NBER recessions, while heads downward and even becomes negative in the late stage of recessions. In particular, $PC2$ attained its minimum of -10.9 in the last quarter of the early 1970s recession. This pattern suggests that there is a lead-lag relation between $PC1$ and $PC2$, which is confirmed in Panel C.

The first four columns of Panel B show the contemporaneous correlations of $PC1$ and $PC2$ with the aforementioned macro variables. $PC1$ has positive correlations with d/p ($\rho = 0.39$) and DEF ($\rho = 0.57$), indicating that $PC1$ tracks valuations of equities and low-grade corporate bonds. As $PC1$ is fairly persistent, this evidence is consistent with the intuition that when perceived future economic conditions are persistently poor, valuations of risky assets decline. $PC2$ has a negative correlations with TERM ($\rho = -0.41$) and a positive correlation with d/p ($\rho = 0.14$), but does not correlate with DEF. Fama and French (1989) find that after 1951, TERM tracked cyclic fluctuations of the aggregate economy at the usual NBER business cycle frequency. Chen (1991) studies the relation between a set of business cycle indicators and real GNP growth. This author finds that DEF and d/p have negative and significant correlations with past growth rates of real GNP, but they predict future real GNP growth up to two quarters ahead. In contrast, TERM does not correlate with past real GNP growth, however, it positively predicts future GNP growth up to five quarters ahead. Estrella and Mishkin (1998) conclude that TERM is one of the most powerful leading financial indicators of NBER recessions. Hence it seems that $PC1$ and $PC2$ carry different information about future economic activity. The conjecture is that $PC1$, mainly correlated with DEF and d/p, summarizes past and current business conditions, while $PC2$, mainly correlated with TERM, contains forward-looking information about future economic activity. Section 3.1 examines this hypothesis and provides supporting evidence.

The rest columns in Panel B report contemporaneous correlations of $PC1$ and $PC2$ with changes in the macroeconomic conditions, including the quarterly excess return on the CRSP value-weighted index (Mkt), and quarterly growth rates of industrial production ($\triangle IP$), real per capita consumption ($\triangle c$), real GDP ($\triangle GDP$), and real per capita labor income ($\triangle l$). Notably, $PC1$ has economically large and statistically significant negative correlations with the growth rates of $\triangle IP$ ($\rho = -0.67$), $\triangle c$ ($\rho = -0.52$), $\triangle GDP$ ($\rho = -0.62$), and $\triangle l$ ($\rho = -0.38$), while $PC2$ has virtually no correlations with these variables. This result highlights the ability of $PC1$ to track current business conditions, while also suggests that $PC1$ and $PC2$ contain different pieces of information. In Panel C, I study the lead-lag relation between $PC1$ and $PC2$ by estimating a first-order vector autoregression (VAR(1)). The "slope" of the term structure, $PC2$, predicts the future "level", $PC1$, but not vice versa. A one-unit change in $PC2$ translates into an almost one-unit change in the future level of the term structure.

3 Information content of the term structure

Recessions are periods with lower real economic activity and heightened economic uncertainty (Bloom, 2014). Given that $PC1$ (level) and $PC2$ (slope) summarize most of the variations of the term structure of recession probabilities, they should forecast real economic activity and economic uncertainty. Besides, most of investors tend to suffer adverse labor income shocks in recessions as they may lose their jobs or small business, therefore $PC1$ and $PC2$ should also forecast future labor income. In this section, I test this hypothesis by performing "in-sample" long-horizon predictive regressions of future growth rates of key macroeconomic quantities on $PC1$ and $PC2$. My goal is not to stress that $PC1$ and $PC2$ are the best predictors by horse-race comparison, but rather to demonstrate the incremental information in $PC1$ and $PC2$ beyond the information in common business cycle indicators.

3.1 Predicting macroeconomic activity and labor income

Following the literature, I measure real economic activity by the growth rates of the industrial production index, real GDP, and real per capita consumption (Fama, 1990; Estrella and Hardouvelis, 1991), and compute the growth rate of real per capita labor income in a way similar to Jagannathan and Wang (1996). I conduct long-horizon predictive regressions of these growth rates on $PC1$ and $PC2$. Because both dependent and independent variables are available quarterly, the sample is quarterly from 1968Q4 to 2015Q1. The specification of the predictive regressions is as follows,

$$y_{t\to t+h} = \alpha(h) + b1(h)PC_1(t) + b2(h)PC_2(t) + \theta(h)X_t + \epsilon_{t,h} \tag{4}$$

where $y_{t\to t+h} \equiv 400/h\ (\log y_{t+h} - \log y_t)$ is the annualized continuously compounded growth rate of y_t from quarter t to quarter $t+h$. The forecasting horizon h takes values of 1, 4, 8, and 12, that is, 1 quarter to 3 years ahead.

The macro control variable X_t includes the term spread, default spread, short-term nominal interest rate proxied by the three-month T-bill rate ($y^{(3m)}$), log dividend-price ratio of the CRSP value-weighted index, and the CRSP value-weighted excess return, all of which are included for their superior ability to forecast real economic activity and labor income (Fama, 1990; Chen, 1991; Estrella and Hardouvelis, 1991; Campbell, 1996; Ang, Piazzesi, and Wei, 2006; Gilchrist and Zakrajšek, 2012, among others). For instance, Estrella and Hardouvelis (1991) find that the term spread predicts the growth rates of real GNP and all its private sector components at horizons of more than two years ahead, and that it outperforms a large set of forward-looking indicators.[7] Finally, X_t also consists of the past

[7]Chen (1991) finds that in univariate regressions, the default spread and dividend-price ratio predict real GNP growth up to two quarters ahead, while the term spread and three-month T-bill rate forecast the growth rate up to four quarters ahead. Ang, Piazzesi, and Wei (2006) model the joint dynamics of the yield curve and real GDP growth as a VAR; their calibration suggests that the term spread, and in particular the short-term nominal rate, must be included together for forecasting future GDP growth. Indeed, there is a long tradition that utilizes the information in the yield curve to predict future macroeconomic activity. See

one-period growth rate $y_{t-1\to t}$ because in Table I, the growth rates of consumption, GDP, and industrial production exhibit non-negligible first-order autocorrelations.

Table IV reports OLS estimates of the predictive regressions. t-statistics of $b(h)$ are adjusted as in Newey and West (1987) with one lag for the one-quarter horizon $h = 1$, and as in Hodrick (1992) for long horizon when the observations of the dependent variables are overlapped. Two sets of estimates are reported, where the control X_t is excluded in the baseline specification (first column within each block) and is included (second column). First, the coefficients of $PC1$ and $PC2$ are almost always negative. Thus $PC1$ and $PC2$ correctly forecast the future movement of real economic activity, either independently or jointly with X_t. Starting with the baseline specification, most of the coefficients of $PC2$ are significantly negative, and their (absolute) magnitudes and associated t-statistics decay very slowly across the horizon. In contrast, $PC1$'s coefficients decline rapidly and lose statistical significance beyond the horizon of eight quarters ahead. Consequently, the impact of $PC2$ is much larger than that of $PC1$ across all horizons. For instance, in the baseline results, at eight quarters ahead a one standard deviation increase of $PC2$ (9.56) is on average associated with -1.33%, -0.35%, -0.63%, and -0.63% drop in the annual growth rate of industrial production, real per capita consumption, real GDP, and real per capita labor income, respectively, ceteris paribus. The corresponding values of $PC1$ are only -0.38%, -0.14%, -0.26%, and -0.17%, respectively. This evidence supports the conjecture in Section 2 that compared with $PC1$, $PC2$ mainly contains information about future long-run macroeconomic conditions.

[**Insert Table IV here**]

The conclusions above barely change when the control X_t is included (second column). For brevity, coefficients of X_t are omitted. The default spread plays a minor role, while the CRSP excess return, and especially the term spread and the short-term interest rate strongly predict macroeconomic activity at all horizons, consistent with the literature. The term spread reduces the predictive power of $PC2$ for industrial production growth and real GDP growth at the horizon of four quarters ahead, but does not affect its power at longer horizons. Notably, in the presence of these leading business cycle indicators, the predictive power of $PC2$ is extended to the horizon of three years ahead. Furthermore, the in-sample $\bar{R}^2s$ are large, suggesting that the variations of the predictable components of future real

Cochrane and Piazzesi (2005), Koijen, Lustig, and Nieuwerburgh (2015), and the references therein.

economic activity, consumption growth, and labor income growth are substantial at the usual business cycle frequency. Specifically, $\bar{R}^2$ for the real GDP growth ranges from 29% ($h = 1$) to 37% ($h = 12$). These magnitudes are consistent with the evidence of Estrella and Hardouvelis (1991). Similar $\bar{R}^2s$ in predictive regressions of industrial production growth on past aggregate stock market returns are documented by Fama (1990).

3.2 Predicting stock market volatility

I then test whether $PC1$ and $PC2$ forecast future economic uncertainty, proxied by expected stock market volatility. The following analyses center on the predictive regressions of the Chicago Board Options Exchange (CBOE) VIX index and long term VIX indices. The squared CBOE VIX index is a model-free estimate of the expected quadratic variation of S&P 500 Index returns over the subsequent 30 days under the risk-neutral measure. The squared long term VIX indices, from Johnson (2015), are model-free estimates of the expected quadratic variations of the S&P 500 Index returns over subsequent 3, 6, and 12 months.[8] In representative-agent equilibrium models, such as the long-run risk models of Bollerslev, Tauchen and Zhou (2009) and Drechsler and Yaron (2011), the expected economic uncertainty is the most important driver of VIX indices. This motivates me to proxy expected economic uncertainty by VIX indices. Empirically, Bloom (2009) demonstrates that a former version of the CBOE VIX index is highly correlated with various measures of economic uncertainty at the both firm- and macro-levels.

I conduct quarterly predictive regressions as follows,

$$\log VIX_{\tau,t+h} = \alpha(\tau,h) + b1(\tau,h)PC_1(t) + b2(\tau,h)PC_2(t) + \theta(\tau,h)X_t + \epsilon_{\tau,t+h} \qquad (5)$$

where t is measured in quarters, the forecasting horizon h is one quarter, $\log VIX_{\tau,t+h}$ is the logarithm of a quarter-$t+h$ VIX index with maturity τ, and $X(t)$ includes quarter-t control variables. Since VIX indices are strictly positive and exhibit large positive skewness, the logarithm transformation renders regression errors close to normal distributions. The

[8] See Johnson (2015) for more details on the long-term VIX data. I thank Travis L. Johnson for making the VIX term structure data available `http://faculty.mccombs.utexas.edu/johnson/data.html`. Technically, VIX indices contain two components, the conditional expected quadratic variations of the S&P 500 Index returns under the physical measure, and a risk premium component (the so-called variance risk premium). I do not differentiate the two components.

samples of the CBOE VIX index and long term VIX indices run from January 1990 to April 2015 and January 1996 to August 2013, respectively, determined by data availability.

[**Insert Table V here**]

Table V reports OLS estimates of the predictive regressions of two specifications. In the first, $X(t)$ includes the term spread, the default spread, and the time-t continuously compounded monthly return on the S&P 500 Index to control for the leverage effect (Black, 1976). Since all VIX indices are highly persistent with first-order autocorrelation coefficients exceeding 0.8, in the second specification $X(t)$ includes an additional variable, the one-period lagged dependent variable. In either specification, $PC1$ is fully subsumed by the default spread, while $PC2$'s coefficients are positively significant for all VIX indices, even after controlling for lagged VIX indices. The economic magnitudes of $PC2$'s coefficients are large. The sample means of the logarithm VIX indices are close to 3 across all maturities. In the first (second) specification, a one standard deviation increase in $PC2$ (9.56) is associated with a 7.3% (3.5%) percentage increase in the three-month VIX index when it is at the sample mean. This evidence suggests that $PC2$ contains incremental information on future expected stock market volatility beyond the information in common business cycle indicators.

The results in this section show that the slope of the term structure of recession probabilities, $PC2$, negatively forecasts future macroeconomic activity as well as labor income, and positively forecasts future expected stock market volatility at all horizons. $PC1$, the level of the term structure, negatively forecasts short- and medium-term future macroeconomic activity and labor income only. Overall these results imply that positive shocks to $PC1$ and especially $PC2$ are bad news to investors that will increase their marginal utility of wealth.

4 Pricing of perceived recession risk

In this section, I study the asset pricing implication of the innovations to the level and slope of the term structure of recession probabilities. I discuss the theoretical motivation of the sign of risk premia on these innovations as risk factors in the cross section and present results of the cross-sectional tests.

4.1 Theoretical prediction

I motivate the sign restriction between the time series and cross section in the context of intertemporal asset pricing models. In the Merton's ICAPM, innovations to state variables that positively forecast future market returns command positive risk premia in the cross section, since exposure to this type of state variable risks cannot helps investors reduce their re-investment risk and better smooth their consumption streams. As Cochrane (2005, Chapter 9) points out, however, the Merton's ICAPM assumes that all sources of wealth, including human capital, are fully marketable. As a result, the only state variables are those that forecast future market returns.

In reality, investors own assets that are not fully marketable, such as human capital (Mayers, 1972; Campbell, 1996; Jagannathan and Wang, 1996, among other). They may lose their jobs or small business, and hence prefer assets whose payoffs are less sensitive to news of future economic downturns to hedge their labor income risk. In equilibrium, this special hedging demand for labor income risk can affect expected asset returns. For instance, in a discrete-time ICAPM in which total wealth comprises stock market wealth and non-marketable human capital, Campbell (1996) demonstrates that innovations to variables that can forecast future stock market returns or labor income are valid risk factors in the cross section. Consequently, variables that forecast future likelihood of recessions in general, labor income in particular, are valid candidates of state variables. State variables of this sort are named as "recession state variables" by Cochrane (2005, Chapter 9).

The evidence in Section 3 collectively shows that an increase in the level ($PC1$) and especially in the slope ($PC2$) of the term structure of recession probabilities is associated with subsequent periods with lower macroeconomic activity, heightened stock market volatility, and lower real labor income growth. Therefore, shocks to $PC1$ and $PC2$ represent important news to future macroeconomic activity and labor market conditions. As a result, $PC1$ and especially $PC2$ are likely to be "recession state variables" of special hedging concern to investors. In the cross section, assets paying more when there are positive shocks to the level or the slope of the term structure are deemed valuable, and investors are willing to accept lower returns on them because they provide insurance against future downside labor income risks. This predicts that the innovations to $PC1$ and $PC2$ should be priced in the cross section with negative market prices of risk.[9]

4.2 Empirical methodology

I test the preceding prediction on the sign of risk premia in the cross section using the two-pass cross-sectional regression (CSR) developed by Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973). While the theoretical argument pins down the sign of risk premia, the empirical analyses quantify the magnitudes of the risk premiums and answer two additional questions. First, do the innovations to $PC1$ and $PC2$ carry negative risk premia in the cross section of asset returns that are both statistically and economically significant? Second, do the innovations to $PC1$ and $PC2$ as risk factors help reconcile the cross-sectional variations of risk premiums on different asset classes?

To proceed, I quantify the innovations to $PC1$ and $PC2$ by a first-order vector autoregression VAR(1),

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1} \tag{6}$$

where $Z_t \equiv (PC1_t, PC2_t)'$. The residual, denoted as $u_t \equiv (\triangle PC1, \triangle PC2)'$ for convenience, contains the innovations to $PC1$ and $PC2$ extracted by the VAR. The estimates of VAR are reported in Panel C of Table III. In the ICAPM literature, VARs are widely used to extract innovations to state variables (Campbell, 1996; Campbell and Vuolteenaho, 2004; Petkova, 2006). Recall that in Table III, the first-order autocorrelations of $PC1$ and $PC2$ are 0.8 and 0.6, respectively; therefore, extracting innovations via VARs avoids the over-difference problem. Figure 4 displays the estimated innovations to $PC1$ and $PC2$. As a comparison, the innovations extracted by the simple first difference are also shown. The two different types of innovations co-move over time with a time series correlation exceeding 0.8. As is evident from the figure, however, the simple difference tends to overstate the magnitudes of innovations after large movements.

[9] An alternative explanation based on the long-run risks model of Bansal and Yaron (2004) yields similar implications. Positive shocks to $PC1$ or $PC2$ are bad news for future aggregate consumption and will raise the current marginal value of wealth of the representative agent if she prefers resolving intertemporal consumption risks sooner—the agent prefers early resolution of uncertainty (Epstein and Zin, 1989). Assets whose payoffs positively covary with shocks to $PC1$ or $PC2$ are deemed valuable because they provide insurance against unfavorable shifts in macroeconomic conditions, or more directly, because their payoffs positively covary with the agent's marginal utility. Consequently, investors are willing to accept lower returns on these assets so that shocks to $PC1$ and $PC2$ are negatively priced. Compared with $PC1$, $PC2$ predicts long-run macroeconomic activity as well as economic uncertainty, and hence, quantitatively, the shock to $PC2$ might be more important in asset pricing than the shock to $PC1$.

I test a three-factor recession risk model using an unconditional two-pass CSR approach. The first factor is market excess return, proxied by excess return on the CRSP value-weighted index (Mkt), and the other two are the innovations to $PC1$ and $PC2$ (extracted via VAR, denoted as $\triangle PC1$ and $\triangle PC2$). The unconditional CSR approach involves two stages. In the first stage, for each asset, its unconditional (or full sample) factor exposures (βs) are estimated by a time series regression of its excess returns on the three risk factors.[10] The excess returns are formed as the actual returns in excess of the return on the three-month T-bill. In the second stage, factors' risk premia are estimated by a single CSR of time series average excess returns of test assets on their full sample factor exposures.

Specifically, let $R^e_{i,t}$ denote excess return on asset i from the period-t-1 to the period-t. The time series regression for each test asset separately yields the unconditional factor exposures β^i_{Mkt}, $\beta^i_{\triangle PC1}$, and $\beta^i_{\triangle PC2}$, respectively.

$$R^e_{i,t} = a_i + \beta^i_{Mkt} Mkt_t + \beta^i_{\triangle PC1} \triangle PC1_t + \beta^i_{\triangle PC2} \triangle PC2_t + \epsilon^i_t,\ i = 1, ..., N \tag{7}$$

The single CSR of time series average excess returns on unconditional factor exposures yields estimated market prices of risk associated with the three factors, denoted as λ_{Mkt}, $\lambda_{\triangle PC1}$ and $\lambda_{\triangle PC2}$, respectively.

$$E_T[R^e_{i,t}] = \alpha + \beta_{i,Mkt}\lambda_{Mkt} + \beta_{i,\triangle PC1}\lambda_{\triangle PC1} + \beta_{i,\triangle PC2}\lambda_{\triangle PC2} + \xi_i,\ i = 1, ..., N \tag{8}$$

where $E_T[R^e_{i,t}]$ denotes the time series average of excess returns on asset i, α refers to the excess zero-beta rate, and ξ_i is the model pricing error of asset i. The key asset pricing restrictions on CSRs are that estimated factors' risk premia should be consistent with theory and are economically and statistically significant in the cross section of different test assets (Lewellen, Nagel, and Shanken, 2010; Adrian, Etula, and Muir, 2014). Further, both the excess zero-beta rate α and individual pricing errors ξ_i should be insignificantly different from zero.

Following the literature, I report several diagnostic statistics for second stage cross-

[10]There are three ways of estimating factor exposures in the first stage, including rolling-window regressions, extending-window, and full sample regressions, all of which are widely used in the literature. See Black, Jensen, and Scholes (1972), Fama and French (1992), Lettau and Ludvigson (2001), and Petkova (2006), among others.

sectional regressions, including the mean absolute pricing error (MAPE, defined as $\frac{1}{N}\sum_{i=1}^{N}|\xi_i|$), adjusted cross-sectional $\bar{R}^2$ (Jagannathan and Wang, 1996) that gauge how well model-implied expected excess returns explain the cross section of average excess returns, and a χ^2 statistic that formally tests the null hypothesis that all individual pricing errors $\{\xi_i\}_{i=1}^{N}$ are jointly zero. To compute the χ^2 statistic, I translate unconditional two-pass CSRs into a set of moment conditions, estimated by a one-stage Generalized Method of Moments (G-MM), and the χ^2 statistic is just the Hansen (1982) over-identification J_T statistic for these moment conditions (Cochrane, 2005, Chapter 12).[11] Because βs in second-stage CSRs are generated regressors, rendering OLS t-statistics biased, I report robust t-statistics, based on the GMM system (t-GMM), that correct the errors-in-variables problem for estimated βs according to Shanken (1992), and that adjust for heteroscedasticity and autocorrelation as in Newey and West (1987) with one lag. Fama-MacBeth (1973) t-statistics (t-FM) adjusted for heteroscedasticity and autocorrelation are also reported.

4.3 Main results

Cross-sectional analysis

I first test the three-factor recession risk model (7-8) in the cross section of the Fama-French 25 size and book-to-market (B/M) sorted portfolios in conjunction with the CRSP value-weighted index.[12] The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). Table VI summarizes the cross-sectional results where the estimated risk premia are reported as percentage per quarter. Specification I shows performance of the CAPM. Although there is large variation of average returns in the cross section, all assets have similar market βs (Fama and French, 1992, 2006).[13] As a result, the CAPM explains only 4% of the cross-sectional variation and the over-identification J_T statistic strongly rejects the CAPM. In specification II, the market price of risk for the innovation to the level of the term structure,

[11] The χ^2 statistic has $N-K$ degree of freedom, where K is the number of explanatory variables in the cross-sectional regressions (including the intercept). The weighting matrix of the GMM system is specified in a way such that the system yields OLS estimates of both first and second stage regressions.

[12] Monthly returns on the 25 portfolios are from Kenneth French's web site, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french`. I thank Kenneth French for making the portfolio data available. The 3-month T-bill return is from CRSP. Monthly returns on test portfolios are compounded into quarterly returns, and quarterly excess returns are formed as returns in excess of the return on the 3-month T-bill.

[13] Because of the multicollinearity problem between the vector of ones and the vector of the market βs (Jagannathan and Wang, 2007), the excess zero-beta rate is large and highly significant, while the risk premium of the market is negative.

$\triangle PC1$, is negative, consistent with the prediction in Section 4.1, but is insignificant. $\triangle PC1$ as an additional factor to the market does not improve the fit, as the cross-sectional $\bar{R}^2$ only slightly increases from 4% to 9%. Specification III and the full recession risk model in specification IV show that the innovation to the slope of the term structure, $\triangle PC2$, is a negatively priced risk factor in the cross section, consistent with how the slope of the term structure predicts future macroeconomic activity and labor income. The magnitude of its risk premium is large, -4.98% (-7.45%) per quarter in specification III (IV).[14] The $\bar{R}^2$s of specification III (57%) and IV (64%) are improved substantially relative to the CAPM and are comparable to the $\bar{R}^2$ of the Fama-French three-factor (1993) model (63%). The J_T statistic does not reject the full model specification. Thus, statistically the three-factor recession risk model captures the cross-sectional variation of average excess returns on the 25 portfolios. One caveat is that the estimated risk premium of $\triangle PC1$ becomes significantly positive in the full model specification, which might be due to the negative correlation between $\triangle PC1$ and $\triangle PC2$.

Figure 5 plots sample average quarterly excess returns on the test assets against their mean excess returns predicted by each model. I label each 25 size and book-to-market sorted portfolios using a two-digit number where the first (second) digit denotes the size (book-to-market) quintile. If a model fits the cross section perfectly, all points should fall on the 45-degree line. The figure echoes the results of cross-sectional $\bar{R}^2$s. In the top left panel, there are large deviations between CAPM-implied expected returns and actual average returns. In contrast, in the bottom left panel, the plot for the recession risk model is much closer to the 45-degree line. The only exception is the "puzzling" low average excess return on portfolio 11 (small and growth stocks), which is also a challenge to the Fama-French three-factor model (bottom right panel).

Hahn and Lee (2006) show that three risk factors, including changes in the default spread ($\triangle DEF$), changes in the term spread ($\triangle TERM$) and market excess return, capture most of the cross-sectional variation of average returns on the 25 portfolios and argue that the size and book-to-market effects are compensation for risks related to variations in credit

[14] The first-stage time series regressions that follow show that the factor exposure of $\triangle PC1$ and $\triangle PC2$ is much smaller than that of market, leading to large estimated market prices of risk. In the literature, inflated market prices of risk of non-traded macroeconomic factors are commonly observed, because embedded "noises" in macro factors that are unrelated to asset returns tend to generate downward biases of estimated factor exposure, and consequently boost estimated market prices of risk (Adrian, Etula, and Muir, 2014).

market conditions and the yield curve. Table III shows that $PC2$ has a significantly negative correlation with $TERM$ ($\rho = -0.41$), therefore it is possible that $\triangle PC2$ is priced because it is correlated with the slope of the yield curve. Conceptually, the two slope variables are different. The term spread reflects not only the expectation about future real economic growth but also the monetary policy (Estrella, 2005; Hahn and Lee, 2006), while the slope of the term structure of recession probabilities mainly reflects the former. Empirically, I examine whether $\triangle PC2$ is still priced in the presence of $\triangle TERM$ and $\triangle DEF$. Specification V shows that $\triangle PC2$ remains a negatively priced risk factor with a quarterly risk premium of -4.7%, the magnitude of which is similar to that in specification III. Thus, $\triangle TERM$ and $\triangle DEF$ do not subsume the pricing power of $\triangle PC2$. Subsection *Model Comparison*, which follows, revisits this issue in more detail.

[**Insert Table VI here**]

An important asset pricing restriction on CSRs, discussed in Section 4.2, is that estimated factors' risk premia should be significant in the cross section of different assets, both economically and statistically (Lewellen et al., 2010). In Table VII, I estimate the recession risk model (7-8) using various equity and bond portfolios to further examine this restriction. In Panel A, I consider 25 size- and book-to-market-sorted portfolios, with 5 corporate bond portfolios sorted by credit spreads. Nozawa (2012) shows that the credit spread is a key bond-level characteristic that strongly predicts future bond excess returns, and there is sizable positive average return spread between portfolios of bonds with high and low credit spreads. In Panel B, the test assets are 25 portfolios double-sorted by size and past long-term returns (past 60 month to 13 month cumulative returns). Fama and French (1996) show that past long-term losers behave as small distressed firms and have larger exposure on their small-minus-big (SMB) and high-minus-low (HML) factors than do past long-term winners. As such, past long-term losers are value stocks and the average return spread between past long-term winners and losers, similar to that between value and growth stocks, can be attributed to the distress premium (Fama and French, 1996). Panel C reports results for 25 portfolios double-sorted by size and investment—measured by growth rate of book value of total assets.[15] Cooper, Gulen, and Schill (2008) and Fama and French (2008) show

[15]The five corporate bond portfolios are from Lettau, Maggiori, and Weber (2014). Nozawa (2012) initially constructs 10 corporate bond portfolios sorted by credit spread. Lettau, Maggiori, and Weber (2014) equally

that asset growth is a strong firm-level characteristics that negatively predict future stock returns, especially for small- and medium-cap stocks. Anderson and Garcia-Feijóo (2006) find that the book-to-market equity ratio is empirically related to past growth rates of firm capital investment. Growth (value) firms tend to accelerate (decelerate) investment two to three years prior to the portfolio formation period. Thus, both past long-term returns and asset growth are firm characteristics closely related to the book-to-market equity ratio. The empirical analysis asks whether the recession risk model can provide a coherent story for observed patterns in these three cross sections.

Not surprisingly, the CAPM (specification I) does a poor job in all cross sections. However, in Panel A, when corporate bond portfolios are included in test assets, the multicollinearity problem between the unit vector and the vector of the market βs is mitigated, and the market becomes a positively priced risk factor. In specification II, the estimated risk premium of $\triangle PC1$ is always negative in each cross section, albeit only significant in Panel A. In addition, $\triangle PC1$ as an additional risk factor to the market only slightly improves the CAPM. Turning to specification III and the full model specification, $\triangle PC2$ is a negative priced risk factor with significant and sizable quarter risk premia, varying from -3.66% to -6.92%. Also, the cross-sectional $\bar{R}^2$s of specification III and the full model are substantially improved, ranging from 48% in Panel A to 60% in Panel C. To summarize, the evidence shows that $\triangle PC2$ is a negatively priced risk factor in a wide array of test portfolios, supporting the theoretical prediction. More importantly, the exposure to the innovation to the slope of the term structure, $\triangle PC2$, plays a critical role in reconciling the cross-sectional variation of risk premia on size, book-to-market, asset growth, and past long-term-return sorted portfolios, as well as corporate bond portfolios sorted by credit spreads.[16]

[**Insert Table VII here**]

weigh the 10 portfolios into 5 portfolios. The data in Panels B and C are from Kenneth French's web site. The 25 size and long-term-reversal (investment) sorted portfolios are constructed through the intersection of five portfolios sorted by market equity and five portfolios sorted by cumulative return over the prior 60 months to 13 months (percentage changes in firms' total assets).

[16]The specification of the three-factor recession risk model is motivated by the recession state variable hypothesis of $PC1$ and $PC2$. As a robustness check, using the same test assets, I test a two-factor specification in which market return is excluded and find that $\triangle PC2$ remains a negatively priced risk factor while $\triangle PC1$ is not priced. However, the cross-sectional $\bar{R}^2$s of the two-factor specification are lower than those of the full model specification, ranging from 24% to 47%.

Lewellen, Nagel, and Shanken's critique

Lewellen, Nagel, and Shanken (2010) criticize the practice of evaluating asset pricing models solely based on how well they explain the cross section of the Fama-French 25 size- and book-to-market-sorted portfolios. These authors emphasize that the 25 portfolios exhibit a strong factor structure since almost all the time series variation of their returns and the cross-sectional variation of their average returns can be captured by the Fama-French three factors. As such, observing a high cross-sectional R^2 and significant factor risk premia of any factor model is not surprising, and is actually a low hurdle. Following Prescription 1 in Lewellen et al. (2010), I conduct cross-sectional tests using excess returns on the 25 portfolios alone or in conjunction with excess returns on the 30 Fama-French industry portfolios to reduce the strong factor structure of the former. I report GLS R^2s of CSRs (Prescription 3 in Lewellen et al.), due to the appealing economic interpretation of the GLS R^2 as a measure of the model's proximity to the mean-variance efficient frontier generated by test assets.

As a comparison, I consider several macroeconomic factor models in Lewellen et al. (2010): i) the conditional consumption-CAPM (CC-CAY) by Lettau and Ludvigson (2001), in which the consumption-wealth ratio CAY is the conditioning variable; ii) the linearized version of the durable consumption-CAPM (DCAPM) by Yogo (2006), where the factors are the market return, the growth rates of durable and nondurable consumption, $\triangle c_{dur}$ and $\triangle c$; iii) the ultimate consumption risk model (U-CCAPM) of Parker and Julliard (2005), where the sole risk factor is the cumulative growth rate of nondurable consumption over the current and subsequent 11 quarters; and iv) the intertemporal CAPM of Hahn and Lee (2006) (HL) introduced previously.[17] In addition, I report results of the CAPM, the Fama-French three-factor model, and the standard consumption-CAPM.

Table VIII summarizes the cross-sectional results where the sample is quarterly from 1969Q1 to 2014Q3, restricted by data availability. The estimated market price of risk for $\triangle PC2$ is -7.52% per quarter ($t = -2.27$) in the cross section of 25 portfolios and drops to -2.99% per quarter ($t = -1.99$) in the larger cross section. Nevertheless, the innovation to the slope of the term structure, $\triangle PC2$, remains a negatively priced risk factor. The finding is not entirely surprising given that there is not much cross-sectional dispersion in

[17]These models are chosen because they are representative macro-factor models that explain the cross-sectional variation of average returns on the 25 size- and B/M-sorted portfolios quite well. Also, CC-CAY and DCAPM are examined by Lewellen et al. (2010).

the average returns on industry portfolios. In contrast, some macro factors priced in the cross section of 25 portfolios lose statistical significance in the larger cross section. Turning to the diagnostic statistics, when the test assets are the 25 portfolios alone, the three-factor recession risk model delivers both the highest OLS $\bar{R}^2$ (64%) and GLS R^2_{GLS} (15%) among all models. When test assets also include the 30 industry portfolios, the recession risk model outperforms other macro-factor models with the OLS $\bar{R}^2$ (20%) and R^2_{GLS} (5%), which are only below the $\bar{R}^2$ (28%) and R^2_{GLS} (7%) of the Fama-French three-factor model. These pieces of evidence lend further support for the prediction in Section 4.1 that $\triangle PC2$ commands a negative risk premium and further suggests that empirically, $\triangle PC2$ is more important than $\triangle PC1$ in accounting for the cross-sectional variation of expected stock returns.

[**Insert Table VIII here**]

Model comparison

The preceding section shows that the recession risk model outperforms some macro-factor models with higher cross-sectional OLS and GLS R^2s. While the R^2 is an intuitive performance measure, in this section, I employ two formal econometric approaches to rigorously compare different asset pricing models.

The first approach is a GMM test based on the Stochastic Discount Factor (SDF) representation of linear factor models, suggested by Cochrane (2005, Chapter 13). The GMM SDF test examines whether one set of risk factors drives out another in the SDF; that is, in the presence of the former, one can ignore the latter for pricing asset returns. Recall that a CSR of average excess returns on βs, such as (8), is based on the beta representation of expected excess returns: $E[R^e] = \beta_f \lambda_f$, where $E[R^e]$ denotes a vector of expected excess returns, and β_f and λ_f are the unconditional factor exposure and market prices of risk for a set of linear factors f, respectively. It is well know that there is an equivalent relation between the beta representation and linear SDFs (Ross, 1978; Dybvig and Ingersoll, 1982). When the test assets are excess returns, the mean of the SDF cannot be identified. A common practice is to specify a normalized linear SDF: $M = 1 - b'[f - \mu_f]$, where μ_f is the mean of f. Consequently the fundamental asset pricing equation $E[MR^e] = 0$ readily implies the following beta representation,

$$E[R^e] = E[R^e(f-\mu_f)^{'}]b = Cov(R^e, f)b = \beta_f \underbrace{Var(f)b}_{\lambda_f} \tag{9}$$

Suppose f can be decomposed into two sets of non-overlapping risk factors f_1 and f_2, i.e., $f \equiv [f_1^{'}, f_2^{'}]^{'}$. Let $M = 1 - b_1^{'}(f_1 - \mu_{f_1}) - b_2^{'}(f_2 - \mu_{f_2})$. The GMM SDF test that examines whether f_2 is driven out by f_1 is simply testing $b_2 = 0$ and the associate Wald statistic $\hat{b}_2^{'}\hat{Var}(\hat{b}_2)^{-1}\hat{b}_2$ follows an asymptotic $\chi^2_{K_2}$ distribution, where K_2 is the number of factors in f_2.[18] Given many established models, I first ask whether in the presence of these risk factors, the coefficient of $\triangle PC2$ in the SDF is zero. This is the very test suggested by Cochrane. Alternatively, I also report Wald statistics testing whether coefficients of (non-overlapping) factors in other models are zero in the SDF given the presence of the three factors in the recession risk model (7-8).

Panel A of Table IX summarizes the results. The test assets are 25 size- and B/M-sorted portfolios, 30 industry portfolios, and the CRSP value-weighted index. I consider the same macro-factor models in the preceding subsection except for the CAPM, which is nested by the recession risk model. The first block presents the Wald statistics, separately for each of the six models, of the null hypothesis that the innovation to the slope of the term structure, $\triangle PC2$, is driven out by factors in other models. For all the six models, the Wald statistic rejects the null hypothesis at the 5% significance level; therefore $\triangle PC2$ does help price test assets, given factors in other models. Similarly, the null hypothesis that both $\triangle PC1$ and $\triangle PC2$ are driven out by other factors is also firmly rejected at the 5% level (untabulated

[18] Cochrane emphasizes that the correct test of the hypothesis is $b_2 = 0$ rather than $\lambda_{f_2} = 0$, where λ_{f_2} is the risk premium of f_2. To calculate the Wald statistic, I form the following two moment conditions, taking into account that the mean of risk factors is estimated.

$$g(b, \mu_f) \equiv \; E\begin{bmatrix} (1 - b_1^{'}(f_1 - \mu_{f,1}) - b_2^{'}(f_2 - \mu_{f,2}))R^e \\ f - \mu_f \end{bmatrix}$$

I estimate the SDF parameters (b, μ_f) by the efficient GMM. The efficient GMM sets $d^{'}S^{-1}g(b, \mu_f)$ to zero, where $d \equiv \frac{\partial g}{\partial [b \;\; \mu_f]^{'}}$ and S is the spectral density matrix of moment conditions. To estimate S, I obtain the time series residuals of moment conditions by plugging in the first-stage GMM estimates of the SDF parameters and estimate S using the Bartlett kernel with a window length of 1. The first-stage GMM uses the following weighting matrix, where I_K is the identity matrix of K dimensions,

$$\begin{bmatrix} Cov(f, R^e) & 0 \\ 0 & I_K \end{bmatrix}$$

results). Conversely, the second block of Panel A shows that among six models, I cannot reject the null hypothesis that risk factors in the CCAPM or in the ultimate consumption risk model (U-CCAPM) can be omitted in the presence of the three factors in the recession risk model. This finding is not entirely surprising because $PC1$ is strongly negatively correlated with contemporaneous consumption growth and $PC2$ predicts future consumption growth up to 12 quarters ahead. To conclude, there is strong evidence that $\triangle PC2$ helps price excess returns on the 56 test assets in the presence of other macro factors.

[**Insert Table IX here**]

Turning to the second approach, I compare different pricing models by the Hansen-Jagannathan (HJ) distance. Hansen and Jagannathan (1997) develop this model mis-specification measure, representing the minimal distance (in the mean-squared metric sense) between a candidate SDF and the set of all admissible SDFs that can price test assets under consideration exactly. The HJ distance is equivalent to the pricing error of the most mis-priced portfolio among all possible portfolios with unit second moments. The appealing interpretation of the HJ distance makes it an economic metric that universally gauges the absolute performance of all asset pricing models. Panel B of Table IX reports squared HJ distances, denoted as δ^2_{model}, for the six macro-factor models, and the difference in squared HJ distances between these models and the recession risk model, denoted as $\delta^2_{model} - \delta^2_{rec}$. The first (second) block presents results for gross returns on the 25 size- and B/M-sorted portfolios and the CRSP value-weighted index (the 25 portfolios, 30 industry portfolios, and the CRSP index). Consistent with the OLS and GLS $\bar{R}^2$s results, the recession risk model has the lowest sample HJ distance (0.375) among all models when the test assets are the 25 portfolios, while in the 56 portfolios, the recession risk model has a lower sample HJ distance (0.920) than all macro-factor models and is outperformed only by the Fama-French three-factor models (0.897). Thus, empirically the recession risk model is closer to the SDF that prices test assets exactly.

To gauge the statistical significance of $\delta^2_{model} - \delta^2_{rec}$, I adopt the tests of Gospodinov, Kan, and Robotti (2013), who develop a general econometric framework to evaluate and compare asset pricing models, either nested or non-nested, based on their sample HJ distances (see also Kan and Robotti, 2009). However, the conclusion here is disappointing. Although there are positive differences in the sample HJ distance between the recession risk model and other models, the tests cannot reject the hypothesis that their HJ distances are equal. Similar to the conclusion in Kan and Robotti (2009), because of the modest sample size on quarterly return data, the returns and risk factors considered seem too noisy to distinguish one model from another in terms of their HJ distances.

Time series analysis

I find that $\triangle PC2$ is an important risk factor in the cross section with a negative market price of risk, and the recession risk model largely captures the cross-sectional variation of average returns on the 25 size- and B/M-sorted portfolios. These two findings together imply that portfolios with higher average returns, such as the small and value stock portfolios, must load more negatively on $\triangle PC2$. The goal of this section is to demonstrate that this is the case and to explore possible explanations.

[**Insert Table X here**]

Table X summarizes time series regressions of the 25 size- and B/M-sorted portfolio returns on the recession risk factors (7). The average quarterly excess returns on these assets in Panel A exhibit pronounced size and B/M effects in my sample period. In each size quintile, high B/M stocks always have higher average excess returns than low B/M stocks, and in most situations, small stocks have higher average excess returns relative to large stocks. Also, the B/M effect is stronger in the small size quintile and the size effect is more salient in the high B/M quintile. Panel E (Panel F) reports factor exposure of the 25 portfolios on $\triangle PC1$ ($\triangle PC2$). Small (Big) and high (low) B/M stocks have negative (positive) factor exposure on $\triangle PC1$, $\beta_{\triangle PC1}$s. However, $\beta_{\triangle PC1}$s across either size or B/M quintile are not in a monotonic fashion. In contrast, consistent with the size and B/M effects, the factor exposure on $\triangle PC2$, $\beta_{\triangle PC2}$s almost always decline monotonically from low B/M stocks to high B/M stocks within each size quintile, and from large stocks to small stocks within each B/M quintile. Put differently, compared with growth (large) stocks, value (small) stocks earn more negative returns when there are positive shocks to the slope of the term structure of recession probabilities. Section 3.1 shows that a heightened slope of the term structure is associated with subsequent periods with lower real aggregate output and labor income. Thus, value (small) stocks pay less precisely when investors revise their beliefs that the aggregate economy will likely enter into a recession in the near future. Notably, $\triangle PC2$ as a priced risk factor is derived from macroeconomic forecasts on business cycles, and hence is less likely correlated with stock-level mispricing. This result lends support to the risk-based explanation for the value premium and complements existing evidence that there are counter-cyclical variations of risk levels in small and value stocks across business cycles (Perez-Quiros and Timmermann, 2000; Lettau and Ludvigson, 2001; Petkova and Zhang, 2005).

Panel F (Panel H) reports t-statistics of estimated factor exposure on $\triangle PC1$ and $\triangle PC2$. Since both of them are macro factors, a concern is that the factor exposure of test assets are insignificantly different from zero, that is, these factors are useless (Kan and Zhang, 1999). However, 12 out of 25 t-statistics of $\beta_{\triangle PC2}$ are above 2. Formally, a likelihood-ratio test of the null hypothesis that the factor exposure $\beta_{\triangle PC1}$s ($\beta_{\triangle PC2}$s) is jointly zero yields a χ^2_{25} statistic of 81.4 (93.4), which strongly rejects the null at any conventional level.

I now explore the source of the cross-sectional difference in factor exposure on the slope of the term structure. Previous studies document that value stocks are relatively distressed (Fama and French, 1993, 1995, 1996) and have higher cash flow risks than growth stocks (Campbell and Vuolteenaho, 2004; Bansal, Dittmar, and Lundblad, 2005; Campbell, Polk, and Vuolteenaho, 2010, among others).[19] The existing evidence, in conjunction with the finding that $PC2$ is a strong predictor of future macroeconomic activity, suggests that the cross-sectional difference in factor exposure on $\triangle PC2$ may be attributed to the higher sensitivity of the cash flows of value stocks to the time variation of investor concern over future recessions.

To examine this conjecture, I measure a firm's cash flows by its profitability, defined as current year operating income before depreciation divided by average total assets of the current and preceding year, namely return on total assets (ROA). I form five B/M-sorted portfolios using all CRSP common stocks following Fama and French (1992). The portfolio-level profitability is the value-weighted ROA of individual firms within each portfolio. I then conduct predictive regressions of changes in the portfolio-level profitability on $PC1$

[19]For instance, using the return decomposition approach, Campbell and Vuolteenaho (2004) find that returns on value stocks have higher exposure on news about future cash flows of the aggregate stock market. Bansal et al. (2005) show that the dividend growth of value stocks is more sensitive to innovations to smoothed aggregate consumption growth. Campbell, Polk, and Vuolteenaho (2010) directly show that the cash flows of value stocks are more sensitive to shocks to aggregate cash flows.

and $PC2$. If the conjecture is true, $PC2$ should negatively predict the cash flows of these B/M-sorted portfolios, and the slope of $PC2$ should decrease in the B/M quintile. Since accounting data is available at the annual frequency, the sample is annually from 1969 to 2013, 45 years in total. The predictive regression is as follows,

$$\overline{\triangle \text{Profit}}^{i}_{t-1\rightarrow t+h-1} = \alpha^{i}(h) + b1^{i}(h)PC_1(t) + b2^{i}(h)PC_2(t) + \epsilon^{i}_{t,h} \tag{10}$$

where time t is measured annually, $\overline{\triangle \text{Profit}}^{i}_{t-1\rightarrow t+h-1} \equiv \frac{100}{h}(\text{Profit}^{i}_{t+h-1} - \text{Profit}^{i}_{t-1})$ is the annualized cumulative change in the profitability of the ith portfolio from year $t-1$ to year $t+h-1$ (in percent), and the forecasting horizon h takes values of 2, 3, and 4.[20] Since the absolute first-order auto-correlation coefficients of the one-period profitability changes $\triangle \text{Profit}_{t-1\rightarrow t}$ for each portfolio are all less than 0.15, mean-reversion of $\triangle \text{Profit}_{t-1\rightarrow t}$ is not a major concern; hence, I do not control for lagged profitability.

Table XI summarizes the results. The slopes of $PC1$ are negative across all forecasting horizons, albeit that they do not decrease monotonically in the B/M quintile. Besides, their magnitudes and associated t-statistics are rather small for the high book-to-market quintile. In contrast, the slopes of $PC2$ are all negative, and are more negative for the high B/M quintile. Thus, the future change in profitability of value stocks is more sensitive to fluctuations in the slope of the term structure, which contains information on future long-horizon macroeconomic activity. Specifically, $PC2$'s coefficients decrease monotonically from -0.011 for the low B/M quintile to -0.021 for the high B/M quintile when the forecasting horizon h is 2 and from -0.017 to -0.029 when h is 3, though the statistical significance of the difference in $PC2$'s coefficients across the B/M quintile cannot be established. Economically, on average, a one standard deviation increase in $PC2$ is associated with 0.11%, 0.14% and 0.21% decline in the annualized profitability for the low, median, and high B/M quintile over two years, $\overline{\triangle \text{Profit}}_{t-1\rightarrow t+1}$. To understand the economic significance, note that the sample means of the one-year profitability change $\triangle \text{Profit}_{t-1\rightarrow t}$ are -0.39%, -0.20% and -0.31% for the low, median, and high B/M quintile, respectively; therefore the effect of a one standard deviation increase in $PC2$ on $\overline{\triangle \text{Profit}}_{t-1\rightarrow t+1}$ is sizable, ranging from 15% to 35% of its sample mean for the low, median, and high B/M quintile, respectively. These findings

[20] Following the convention in the literature, I assume that accounting information for year-$t-1$ is available at the end of June at year-t. Thus, I use $PC1$ and $PC2$ at the end of June at year-t to predict annualized cumulative changes in profitability from year-$t-1$ to year-$t+h-1$, where $h \in \{2, 3, 4\}$.

support the hypothesis that $PC2$ negatively predicts the future cash flows of B/M-sorted portfolios and that the coefficient of $PC2$ is decreasing in the B/M quintile.

[**Insert Table XI here**]

4.4 Factor mimicking portfolios

Because the innovations to the level and slope of the recession probability term structure are non-traded macro factors, I construct two factor-mimicking portfolios (FMPs) to track these innovations by projecting them into a space of excess returns on traded assets, following Breeden, Gibbons, and Litzenberger (1989). This approach is frequently used for non-traded macro factors and allows me to expand the data to monthly frequency and a longer sample period, which serves as "out-of-sample" tests for the recession risk model (e.g., Vassalou, 2003; Jagannathan and Wang, 2007; Adrian, Etula, and Muir, 2014).

FMPs are excess returns. One asset pricing restriction is that the intercepts (i.e., alphas) in time series regressions (7) should be jointly zero if the risk factors therein can span the space of test assets in the mean-variance sense. I report the Gibbons, Ross, and Shanken (1989) (GRS) F-test statistic, which formally gauges the joint significance of the intercepts. Economically, the GRS statistic measures the degree of proximity of the maximum squared Sharpe ratio generated by the candidate risk factors to the maximum squared Sharpe ratio generated by test assets in conjunction with the candidate factors. After taking the sampling variation into account, the former should not deviate significantly from the latter if the candidate factors are indeed on the mean-variance efficient frontier. Statistically, the GRS time series test is equivalent to a GLS CSR with (traded) factors included as additional test assets, which forces the cross-sectionally estimated factor risk premia to equal their time series means. Thus, factor risk premia are not free parameters in GRS time series tests, but rather are constrained, a prescription also suggested by Lewellen et al. (2010).

Specifically, I run the following full-sample linear projection regressions,

$$y_t = a + b' X_t + \epsilon_t, \ y_t \in \{\triangle PC1_t, \triangle PC2_t\} \tag{11}$$

b, the portfolio weight, is estimated by OLS. Since the return space contains excess returns only, the weights need not be normalized. $b' X_t$, the corresponding FMPs, can be interpreted as the portfolios formed by the basis assets that have the maximum in-sample correlation with $\triangle PC1$ and $\triangle PC2$.

X_t is given by $[BL, BM, BH, SL, SM, SH, b1, b4, b5, corpr]$, where the first six variables denote the six Fama-French size (Small and Big) and B/M (Low, Medium, and High) sorted portfolios used to construct the Fama-French three factors. $b1$, $b4$, and $b5$ refer to the three Fama bond portfolios sorted by maturity, which comprise T-bills with maturities of 0-1, 3-4, and 4-5 years, respectively, and $corpr$ is the Ibboston long-term corporate bond portfolio, which comprises investment-grade corporate bonds with maturity of more than 10 years.[21] The 6 Fama-French size- and B/M-sorted portfolios are chosen because they span a large amount of return spaces. From Table III, $PC1$ is significantly correlated with the default spread and $PC2$ is significantly related to the term spread. Thus, the T-bill and corporate bond portfolios are chosen because they help track the innovations to $PC1$ and $PC2$.

The estimated portfolio weights are as follows,

$$b_{\triangle PC1} = [-0.07, -0.35, -0.05, 0.39, -0.58, 0.02, 12.53, -1.85, 0.83, 0.33]$$
$$b_{\triangle PC2} = [-0.02, 0.39, -0.15, 0.19, -0.48, -0.03, -3.05, 3.23, -1.77, -0.22]$$

The correlation between $\triangle PC1$ ($\triangle PC2$) and its FMP, $\triangle PC1\ FMP$ ($\triangle PC2\ FMP$) is 0.47 (0.34). From the portfolio weights, $\triangle PC1\ FMP$ takes long positions in small and low book-to-market stocks (SL), long-term corporate bonds (corpr), and the short-term T-bills (b1), while it takes short positions in two medium book-to-market portfolios (SM and BM). $\triangle PC2\ FMP$ sells short the small and medium book-to-market portfolio (SM) and takes a long position on the big and medium book-to-market portfolio (BM), so that $\triangle PC2\ FMP$ negatively captures the value premium. In addition, $\triangle PC2\ FMP$ load on term premium via taking a long position on the Treasury bond portfolio with maturity between three and four years (b4) and selling short the short-term T-bill portfolio (b1).

[**Insert Table XII here**]

Table XII presents summary statistics of the two FMPs as well as the Fama-French three factors, Mkt, SMB, and HML. Panel A reports their quarterly time series moments

[21] The Ibboston long-term corporate bond returns are from the website of Amit Goyal `http://www.hec.unil.ch/agoyal/docs/PredictorData2015.xlsx`. I thank Amit Goyal for making the corporate bond returns data available.

and annualized Sharpe ratios. The mean of $\triangle PC1$ FMP is 0.29% per quarter, which is slightly positive but not significant ($t = 0.55$). In contrast, $\triangle PC2$ FMP has a significantly negative quarterly mean -0.77% ($t = -4.3$). This finding is consistent with cross-sectional results that the $\triangle PC1$ is not priced but $\triangle PC2$ is negatively priced. The Sharpe ratio of $\triangle PC1$ FMP is tiny, while $\triangle PC2$ FMP has a Sharpe ratio of -0.59, the absolute magnitude of which is greater than the Sharpe ratios of market excess return (0.35), SMB (0.19), and HML (0.35). Thus, $\triangle PC2$ FMP represents an attractive risk-return tradeoff. Panel B reports the correlation between the two FMPs and the Fama-French three factors. Both $\triangle PC1$ FMP and $\triangle PC2$ FMP are strongly negatively associated with the market and SMB, but only $\triangle PC2$ FMP has a significant negative correlation with HML ($\rho = -0.29$). The time series regressions in Panel C show that $\triangle PC2$ FMP has a CAPM α of -0.59% per quarter ($t = -3.42$) and a Fama-French three-factor model α of -0.29% per quarter ($t = -2.34$); therefore, $\triangle PC2$ FMP is not mean-variance spanned by market return or Fama-French three factors (FF3). Panel D reports GRS statistics on the 25 size- and B/M-sorted portfolios for four different models, CAPM, FF3, the market with $\triangle PC2$ FMP (Mkt+$\triangle PC2$ FMP), and finally the market with $\triangle PC1$ FMP and $\triangle PC2$ FMP ("Rec FMP"). The latter two specifications of the recession risk model substantially improve the CAPM and have GRS statistics close to that of FF3; nonetheless, the GRS statistics reject all four models.

[**Insert Table XIII here**]

Table XIII summarizes CSRs on the 25 size- and B/M-sorted portfolios in conjunction with the Fama-French 10 industry portfolios for four different models considered in Panel D of Table XII. The sample is at monthly frequency and starts from July 1963, which coincides with the common starting period in the literature, because of the reliability of Compustat accounting data. To ease interpretation, all variables are again reported in percentage terms per quarter. Again, the CAPM (first column) does a poor job. Turning to the third column of the full model specification "Rec FMP", $\triangle PC2$ FMP is priced and carries a negative risk premium, -0.58% per quarter, while $\triangle PC1$ FMP is not priced. The OLS cross-sectional R^2, $\bar{R}^2_{OLS}$, of "Rec FMP" (57%) improves substantially relative to the CAPM (-3%) and is greater than $\bar{R}^2_{OLS}$ of FF3 (51%). The conclusion for GLS R^2_{GLS}s is similar, suggesting that Rec FMP is closer to the mean-variance efficient frontier spanned by the test assets than

FF3. In the last column, I consider a two-factor specification including market and $\triangle PC2$ FMP. Removing the FMP of $\triangle PC1$ barely changes the estimated market price of risk of $\triangle PC2$ FMP, -0.59% per quarter, and does not reduce the cross-sectional R^2. Regarding the GRS tests, "Rec FMP" and the two-factor specification perform slightly worse than FF3. Overall, consistent with previous quarterly results in Table VI, the results of the post-1963 monthly sample suggest that $\triangle PC2$ is an important priced risk factor and helps reconcile the size and value premia.

4.5 Currencies and equity index options

Ideally, an asset pricing model should apply to *all* assets, however, empirical asset pricing tests often focus on some particular asset classes. Lettau, Maggiori, and Weber (LMW, 2014) find that the downside risk CAPM (DCAPM), which is the static CAPM in conjunction with a market downside risk factor, can jointly reconcile excess returns on various asset classes: equities, equity index options, currencies, commodities, and sovereign bonds. This section examines the pricing performance of the factor mimicking portfolios of the recession risk model, "Rec FMP", in the cross section of S&P 500 Index options' returns and developed countries' currency returns. I focus on these two asset classes because their returns vary substantially across business cycles and are known to be exposed to cyclical risk factors, such as durable consumption growth or downside market risk. For instance, Lustig and Verdelhan (2007) rationalize the cross-sectional variation of average foreign currency returns via differences in their exposures to U.S. durable consumption growth. Dahlquist and Hasseltoft (2015) find that past country-level economic fundamentals, like industrial production and trade balance, have strong predictive power for future currency returns. Besides, recently these two asset classes have attracted a lot of attention and debate on whether their returns can be explained by exposure to systematic risk factors.[22]

I first investigate whether "Rec FMP" can explain the cross section of S&P 500 Index option returns. Data for S&P 500 Index option returns are from Constantinides, Jackwerth and Savov (2013) (CJS hereafter). CJS construct a large panel of 54 leverage-adjusted S&P 500 Index option portfolios and compute their monthly returns from April 1986 to January

[22]See Constantinides, Jackwerth, and Savov (2013) for S&P 500 Index option returns. See Daniel, Hodrick, and Lu (2014), Lustig and Verdelhan (2007), Burnside et al. (2011), and Dobrynskaya (2014) for the relation between returns to currency carry trade strategies and consumption or market downside risks.

2012, 288 months in total. Each portfolio is daily adjusted to have a CAPM beta close to 1 and to maintain constant maturity (30, 60, and 90 days) and moneyness (the strike-to-spot ratio).[23] Such leverage adjustment reduces volatility and other higher moments of option returns, which renders linear factor models more applicable. For more details about the option data, please refer to the original CJS paper.

[**Insert Table XIV here**]

Table XIV presents cross-sectional results of "Rec FMP" using S&P 500 Index option portfolios and 25 size- and B/M-sorted portfolios as test assets. Since CJS's option returns are highly correlated across maturity and moneyness, following LMW (2014), I select 18 option portfolios that comprise an equal number of call and put options with the same maturities of 30 days, 60 days, and 90 days, and spot-to-strike ratios of 0.9, 1, and 1.1, respectively. I consider the FF3 and the DCAPM as benchmarks.[24]

The left panel reports the results using the 18 option portfolio returns and the market excess return. I impose the constraint that the excess zero-beta rate is zero to increase the power of the cross-sectional test, since preliminary analysis shows that even the CAPM performs well without this constraint. Starting with "Rec FMP", both the market excess return factor and the $\triangle PC2\ FMP$ factor are priced with correct signs of market prices of risk, whereas the risk premium of $\triangle PC2\ FMP$ is more than three times the estimated risk premium using stock returns only. Consistent with LMW, the market excess return factor and the downside market factor have positive risk premia. Importantly, the pricing performance of "Rec FMP" is comparable to that of the DCAPM. "Rec FMP" has a MAPE of 0.32, which is lower than the MAPE of 0.38 for the DCAPM, while its cross-sectional $\bar{R}^2$, 0.89, is slightly higher than the $\bar{R}^2$ of the DCAPM. The FF3 model also has good cross-sectional performance in terms of low MAPE and high $\bar{R}^2$, however, the estimated market prices of risk reveal that the FF3 model has difficulty reconciling the cross-sectional variation of option returns. The SMB factor has a market price of risk of 8.25% per quarter, which is

[23]Note that by construction, returns on put option portfolios are derived from selling put options.

[24]My empirical implementation of the downside CAPM is slightly different from LMW (2014) in two dimensions. First, I use simple excess returns of test assets and factors instead of log excess returns as in LMW. Second, unlike LMW, I do not impose the constraint that the cross-sectional market price of risk for the market excess return factor is equal to its time series mean. However, this does not mean that, in my implementation, the market risk premium is a free parameter, because I include the market excess return itself as a test asset. In brief, the constraint that I impose is less strict than that imposed by LMW, and consequently the DCAPM under my implementation may have better performance.

implausibly higher than its time series average, and the HML factor has a counter-factually negative market price of risk. The large J_T statistics for all three models indicate that they are all mis-specified. Figure 6 displays the predicted versus realized excess returns of the 19 test assets. As is evident from the figure, no model can reconcile the well-documented large average return from selling the 30-day, deep, out-of-money put option.

The right panel reports results using the 18 option portfolio returns, 25 size- and B/M-sorted portfolios, and the CRSP market excess return—44 test assets in total. Because the cross-sectional variation of expected returns is large, I drop the constraint that the excess zero-beta rate is zero. Starting with the column marked "Rec FMP", both $\triangle PC1\ FMP$ and $\triangle PC2\ FMP$ are significantly priced in the cross section with negative market prices of risk of -3.86% and -0.81% per quarter, which lends further support to the previous theoretical prediction, albeit that the risk premium of $\triangle PC1\ FMP$ is too high relative to its time series mean. The DCAPM performs well in the cross-section of equity and equity index option returns. The downside market factor is priced and its risk premium, 4.19% per quarter, does not change substantially from the risk premium, 4.63% per quarter, estimated using options only. CJS also find that a specification similar to the DCAPM with market prices of risk that are constrained to equal the prices of risk estimated in the cross section of stock returns performs very well in the joint cross section of equity and equity index option returns. Regarding diagnostic statistics, "Rec FMP" underperforms the DCAPM with a slightly larger MAPE, a lower $\bar{R}^2$, and a significantly negative zero-beta rate.

I then examine whether $\triangle PC2\ FMP$ is priced in the cross section of currency returns and whether "Rec FMP" can reconcile the cross-sectional variation of currency risk premia. The sample of currency returns is monthly from January 1974 to March 2010, also from LMW (2014). LMW construct five interest rate-sorted portfolios of currencies of developed countries.[25] For each portfolio, LMW compute its monthly bilateral log return in excess of the log return on the U.S. dollar. More specifically, each portfolio is a zero-cost portfolio that longs currencies of developed countries other than the U.S., while funding the position by borrowing U.S. dollars. Such a zero-cost trading strategy is the so-called carry trade in the literature. It is well known that the risk-free interest rate of each country is the

[25] LMW also construct another set of currency portfolios formed by currencies of both developed and developing countries. The cross-sectional results of using these currency portfolios are qualitatively similar to the results shown in the main text.

most informative characteristic that predicts the cross-sectional variation of currency returns (Lustig, Roussanov, and Verdelhan, 2011). Indeed, the five interest rate-sorted currency portfolios have monotonically increasing average returns.

[**Insert Table XV here**]

Table XV presents the pricing results of "Rec FMP" on the cross section of currency and stock excess returns. The left panel reports the cross-sectional tests using the five currency portfolios and the market excess returns. I impose the constraint that the excess zero-beta rate is zero, to increase the power of the test. Starting with the column marked "Rec FMP", similar to the pricing results of index option returns, both the market factor and $\triangle PC2\ FMP$ are priced in the cross section with correct signs of market prices of risk. The risk premium of $\triangle PC2\ FMP$ is negatively significant and economically large, -3.07% per quarter. Interestingly, compared to the DCAPM, although "Rec FMP" has a relatively higher MAPE of 0.33 and a lower cross-sectional $\bar{R}^2$ of 0.6, it is not rejected by the J_T test at the 5% significance level. The cross-sectional pricing performance of the FF3 model is poor. Both the size and value factors are not priced and the model has a large MAPE of 0.4. This finding is consistent with previous studies which document that currency carry trade strategies have only limited unconditional exposure to equity market risks, measured by the factor exposures on the Fama-French three-factor model (Lustig and Verdelhan, 2007; Burnside et al., 2011; Daniel, Hodrick, and Lu, 2014).

The right of the table panel presents the pricing results of "Rec FMP" on the joint cross section of the 5 currency portfolios, the 25 size- and B/M-sorted portfolios, and the CRSP value-weighted index—31 test assets in total. I drop the restriction that the excess zero-beta rate is zero, as the cross-sectional variation of risk premia is large. Starting with the column marked "Rec FMP", both $\triangle PC1\ FMP$ and $\triangle PC2\ FMP$ are significantly priced in the cross section with large market prices of risk of -3.91% and -0.85% per quarter. The estimated market prices of risk for $\triangle PC1\ FMP$ and $\triangle PC2\ FMP$ are very close to those estimated from the joint cross section of index options and stock returns, shown in the right panel of Table XIV. The cross-sectional diagnostic statistics in Panel B reveal that "Rec FMP" performs uniformly better than the DCAPM and the FF3 model, with the only exception that the excess zero-beta rate of "Rec FMP" is higher and significantly positive. "Rec FMP" has the smallest MAPE of 0.32 and the largest cross-sectional $\bar{R}^2$ of 0.81 among the three models . Figure 9 graphs the predicted versus realized excess returns of the 31 test assets. The 31 test assets under "Rec FMP" fall closer to the 45-degree line than do the test assets under the DCAPM and the FF3 model.

To conclude, the innovation to the slope of the term structure $\triangle PC2$, is negatively priced in the cross-section of equity, equity index option and currency returns and helps explain the cross-sectional variation of average returns on these asset classes. The factor mimicking portfolios of the recession risk model have comparable performance to the DCAPM of Lettau, Maggiori, and Weber (2014). Thus the recession risk model has a potential to offer a risk-based explanation for the joint cross section of returns on the three asset classes. Because $\triangle PC2$ measures the slope of term structure of investors' perceived recession probabilities, the findings suggest that time-varying investor concern over future recessions might be a common economic force in driving risk premia of these asset classes.

5 Conclusion

Motivated by the observation that the duration of economic recessions varies over time, this paper studies a new macro-factor model, which links risk premia to investor concern over recessions, measured by the term structure of recession probabilities from the Survey of Professional Forecasters. I find that the innovation to the slope of the term structure is negatively priced with an economically large and significant risk premium in a wide range of test assets, consistent with how the slope predicts long-run macroeconomic activity and labor income. A three-factor recession risk model, including market excess return and the innovations to the level and slope of the term structure, explains a substantial fraction of the cross-sectional variation of average returns on portfolios sorted on firm characteristics such as size, book-to-market equity, and asset growth. These findings are robust to the critique raised by Lewellen, Nagel and Shanken (2010) on testing linear factor models. Furthermore, GMM Stochastic Discount Factor tests indicate that the innovation to the slope of the term structure helps price the test assets in the presence of factors in other models such as the Fama-French (1993) three-factor model and the conditional CCAPM of Lettau and Ludvigson (2001).

I argue that the innovation to the slope is a negatively priced risk factor because the slope is a recession state variable in the sense of Cochrane (2005, Chapter 9) that predicts future macroeconomic activity and labor market conditions, instead of future market returns. Investors may lose their jobs and business in recessions and hence prefer assets whose cash flows are less sensitive to news of future recessions to specifically hedge their labor income risks. I find that returns on value firms, small firms, past long-term losers, and low quality corporate bonds load more negative on the innovation to the slope of the term structure than returns on growth firms, large firms, past long-term winners, and high quality corporate bonds. In addition, future profitability changes of value firms are more sensitive to temporal variations in the slope of the term structure than growth firms. Consequently, investors are less willing to hold risk assets such as value and small firms because they cannot help investors better smooth their consumption and hedge their labor income risks. These pieces of evidence are consistent with the recession state variable explanation for the slope. I also show that the factor mimicking portfolios of the model help explain the joint cross section of average returns on equities, equity index options, and currencies and have comparable pricing performance to the downside risk CAPM of Lettau, Maggiori, and Weber (2014). Overall, my findings support the risk-based explanation of the value premium and suggest that an economic source of risk premia on test assets can be attributed to time-varying investor concern over future recessions that is priced.

Finally, this paper studies particular macroeconomic forecasts—recession probabilities from the SPF. However, there is a wide range of macroeconomic announcements and forecasts of say, inflation and unemployment, at the information age. How to make use of all these information jointly and optimally for macro-factor models could be a fruitful future research area.

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Table I: **Descriptive Statistics of SPF Recession Probabilities**

This table reports descriptive statistics (in percentage terms) of recession probability forecasts, taken from the Survey of Professional Forecasters (SPF), and other macroeconomic variables used in empirical analyses. $Rec_{t,i}, i \in \{0,1,2,3\}$ refers to the probability of a decline in U.S. real GDP in quarter-$t+i$, forecast at quarter-t. Mathematically, $Rec_{t,i}$ is defined as $Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1})$, where GDP_{t+i} denotes the level of U.S. real GDP in quarter-$t+i$. The macroeconomic variables include the term spread (TERM), default spread (DEF), the log dividend-price ratio on the CRSP value-weighted index (d/p), the quarterly excess returns on the CRSP value-weighted index (Mkt), and growth rates of the industrial production index ($\triangle IP$), quarterly real per capita consumption ($\triangle c$), quarterly real GDP ($\triangle GDP$), and quarterly real per capita labor income (l), all of which are seasonally adjusted, as introduced in Section 2. Panel A displays the sample moments of recession probabilities and macroeconomic variables, including mean, standard deviation, median, skewness, kurtosis, minimum, maximum, first-order autocorrelation ($AC(1)$), and fifth-order autocorrelation ($AC(5)$). Panel B reports their time series correlations. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters in total.

Panel A: Descriptive Statistics (%)

	Mean	Std	Median	Skew	Kurt	Min	Max	AC(1)	AC(5)	Obs
Recession Probabilities										
Rec_0	19.21	22.92	9.66	1.83	2.41	0.52	94.41	0.74	0.06	186
Rec_1	19.24	16.33	12.85	1.73	2.53	2.16	74.78	0.78	0.14	186
Rec_2	18.10	10.66	15.27	1.72	3.04	4.03	58.80	0.77	0.18	186
Rec_3	17.20	6.53	16.43	0.86	0.70	4.56	36.31	0.77	0.29	186
Rec_4	17.27	5.86	16.74	0.51	-0.29	4.51	33.34	0.78	0.41	182
Macro Variables										
$\triangle IP$	0.55	1.65	0.74	-1.57	5.14	-7.31	4.13	0.48	-0.14	186
$\triangle c$	0.44	0.44	0.46	-0.45	0.92	-1.12	1.55	0.52	0.06	186
$\triangle GDP$	0.68	0.82	0.73	-0.30	2.05	-2.14	3.81	0.32	-0.03	186
$\triangle l$	0.33	0.85	0.38	-0.49	1.92	-2.96	3.27	0.02	-0.03	186
TERM	1.11	1.21	1.21	-0.40	-0.07	-3.07	3.33	0.86	0.44	186
DEF	1.10	0.45	0.96	1.84	4.77	0.55	3.38	0.84	0.37	186
d/p	0.99	0.42	1.02	-0.14	-0.91	0.11	1.77	0.98	0.87	186
Mkt	1.54	8.87	2.33	-0.48	0.59	-26.85	23.37	0.07	0.01	186

Panel B: Correlation Matrix

	Rec_1	Rec_2	Rec_3	Rec_4	$\triangle IP$	$\triangle c$	$\triangle GDP$	$\triangle l$	TERM	DEF	d/p	Mkt
Rec_0	0.90	0.68	0.35	-0.05	-0.65	-0.48	-0.62	-0.34	-0.06	0.57	0.36	-0.06
Rec_1	1.00	0.89	0.55	0.09	-0.66	-0.53	-0.59	-0.38	-0.19	0.55	0.39	-0.10
Rec_2	0.89	1.00	0.80	0.35	-0.56	-0.48	-0.48	-0.37	-0.35	0.40	0.40	-0.12
Rec_3	0.55	0.80	1.00	0.79	-0.39	-0.32	-0.31	-0.27	-0.43	0.25	0.37	-0.11
Rec_4	0.09	0.35	0.79	1.00	-0.08	-0.01	0.02	-0.02	-0.36	0.08	0.29	-0.10

Table II: **Forecasting NBER Recessions (Q4/1968-Q2/2014, 183 Quarters)**

This table reports the maximum likelihood estimates and associated z-statistics (in parentheses) of probit predictive regressions of future NBER recession dummies on current SPF recession probability forecasts (in percentage terms). The dependent variable $D_{t+i},\ i \in \{0,1,2,3\}$ is a dummy that is defined as follows,

$$D_{t+i} = \begin{cases} 1, \text{quarter } t+i \text{ is in an NBER recession} \\ 0, \text{otherwise} \end{cases}$$

The probit regression is specified as follows,

$$p_{t,i} \equiv Pr(D_{t+i} = 1|\mathcal{F}_t) = \Phi(\beta_0 + \beta_1 Rec_{t,i} + \beta_2 Rec_{t,i+1} + \gamma X_t)$$
$$\log \ell = \sum_{t=1}^{T} D_{t+i} log p_{t,i} + (1 - D_{t+i}) log(1 - p_{t,i})$$

where $Pr(D_{t+i} = 1|\mathcal{F}_t)$ is the probability that quarter-$t+i$ is in an NBER recession, conditional on quarter-t information $\mathcal{F}_t$, Φ is the cumulative distribution function of the standard normal and X_t are control variables including the observations of the term spread (TERM) and the CRSP value-weighted index return (Mkt) in quarter-t. The main explanatory variables are $Rec_{t,i}$ and $Rec_{t,i+1}$, where $Rec_{t,i}$ refers to the quarter-t SPF forecasts of the probability of a decline in U.S. real GDP level in quarter-$t+i$. $\log \ell$ is the log likelihood function of the model. HL (p-value) is the p-value of the Hosmer-Lemeshow χ^2 statistic testing the goodness-of-fit of the regression. Pseudo R^2 is defined by Estrella and Mishkin (1998), which takes a value between 0 ("no fit") and 1 ("perfect fit"). The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the second quarter of 2014 (2014Q2), 183 quarters in total.

	SPF Only				SPF & Controls		
	D_t	D_{t+1}	D_{t+2}	D_{t+3}	D_{t+1}	D_{t+2}	D_{t+3}
$Rec_{t,0}$	**0.047**						
z-stat	(3.86)						
$Rec_{t,1}$	0.011	**0.053**			**0.070**		
z-stat	(0.61)	(3.40)			(3.88)		
$Rec_{t,2}$		0.000	**0.078**		-0.025	**0.082**	
z-stat		(0.00)	(4.13)		(0.89)	(3.75)	
$Rec_{t,3}$			-0.051	**0.052**		**-0.083**	0.012
z-stat			-(1.58)	(3.09)		(2.24)	(0.60)
TERM					-0.202	**-0.378**	**-0.581**
z-stat					-(1.53)	-(2.93)	-(4.38)
Mkt					**-0.066**	**-0.069**	**-0.041**
z-stat					-(3.87)	-(4.10)	-(2.67)
Pseudo R^2	0.53	0.33	0.18	0.05	0.47	0.38	0.26
HL (p-value)	0.14	0.17	0.13	0.08	0.57	0.91	0.73
Obs	183	182	181	180	182	181	180

Table III: **Descriptive Statistics of Principal Components of the Term Structure of SPF Recession Probability Forecasts**

This table reports summary statistics of the first and second principal components, $PC1$ and $PC2$, of the term structure of SPF recession probabilities (in percentage terms). Panel A displays the sample moments, including mean, standard deviation, median, skewness, kurtosis, minimum, maximum, and first-order autocorrelation $AC(1)$ (whole sample only) over the whole sample and over recessions identified by the NBER. Panel B reports the contemporaneous correlations and p-values (in parentheses) of $PC1$ and $PC2$ with macroeconomic variables, including the term spread (TERM), default spread (DEF), log dividend-price ratio on the CRSP value-weighted index (d/p), quarterly excess returns on the CRSP value-weighted index (Mkt), and quarterly growth rates of the industrial production index ($\triangle IP$), quarterly real per capita consumption ($\triangle c$), final revised quarterly real GDP ($\triangle GDP$), and quarterly real per capita labor income (l), all of which are seasonally adjusted, as described in Section 2. Panel C reports the estimation results of the VAR(1) model of $PC1$ and $PC2$. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters in total.

Panel A: Sample Moments of Principal Components

	Mean	Std	Median	Skew	Kurt	Min	Max	AC(1)	Obs
All									
PC1	32.79	28.94	20.63	1.76	2.46	4.19	130.29	0.79	186
PC2	15.41	9.56	14.6	0.75	2.38	-10.94	51.47	0.59	186
NBER Recessions									
PC1	82.64	28.27	74.49	0.31	-1.27	41.08	130.29	-	29
PC2	11.84	13.59	10.03	0.62	0.14	-10.94	46.37	-	29

Panel B: Contemporaneous Correlation with Macro Variables

	TERM	DEF	d/p	Mkt	$\triangle IP$	$\triangle c$	$\triangle GDP$	$\triangle l$
PC1	-0.15	0.57	0.39	-0.08	-0.67	-0.52	-0.62	-0.38
p-value	(0.05)	(0.00)	(0.00)	(0.27)	(0.00)	(0.00)	(0.00)	(0.00)
PC2	-0.41	-0.07	0.14	-0.10	-0.03	-0.10	0.05	-0.11
p-value	(0.00)	(0.32)	(0.05)	(0.18)	(0.64)	(0.18)	(0.54)	(0.14)

Panel C: VAR(1) of Principal Components

	$PC1_{t+1}$	$PC2_{t+1}$
Intercept	-7.64	8.69
t-stat	-(3.12)	(7.13)
$PC1_t$	0.78	-0.06
t-stat	(20.25)	-(3.31)
$PC2_t$	0.97	0.57
t-stat	(8.33)	(9.90)
$\bar{R}^2$	0.72	0.37
Obs	185	185

Table IV: **Forecasting Real Economic Activity and Labor Income Growth (Q4/1968-Q1/2015, 186 Quarters)**

This table reports ordinary least square (OLS) estimates, t-statistics (in parentheses), and adjusted OLS R-squares $\bar{R}^2s$ of predictive regressions of future quarterly growth rates of the industrial production index, real per capita consumption, real GDP, and real per capita labor income on $PC1$ and $PC2$. $PC1$ and $PC2$ are the first principal component (level) and the second principal component (slope) of the term structure of SPF recession probabilities (in percentage terms). The industrial production index (IP), real per capita consumption (c), real GDP (GDP), and real per capita labor income (l) are quarterly and seasonally adjusted. The predictive regression is specified as follows,

$$y_{t\to t+h} = \alpha(h) + b1(h)PC_1(t) + b2(h)PC_2(t) + \theta(h)X_t + \epsilon_{t,h}$$

where $y_{t\to t+h} \equiv 400/h$ (log y_{t+h} − log y_t) is the annualized continuously compounded growth rate of y_t from quarter t to quarter $t+h$. The macro control variable X_t consists of the term spread (TERM), default spread (DEF), three-month T-bill rate ($y^{(3m)}$), CRSP value-weighted index excess return (Mkt), log dividend-price ratio on the CRSP value-weighted index (d/p), and lagged one-period growth rate $y_{t-1\to t}$. "Y" ("N") in the row labeled "Macro Control" refers to a model specification where X_t is included (excluded) in the regression. The definition of macro variables is introduced in Section 2. The sample of predictive regressions is quarterly from 1968Q4 to 2015Q1. The forecasting horizon h takes values of 1, 4, 8, and 12. t-statistics (in parentheses) are adjusted by Newey and West (1987) standard errors with one lag when the forecasting horizon h is 1, and by the Hodrick (1992) standard errors for $h > 1$ when the observations of dependent variables are overlapped.

Panel A: Industrial Production Index Growth

	$\triangle IP_{t\to t+1}$		$\triangle IP_{t\to t+4}$		$\triangle IP_{t\to t+8}$		$\triangle IP_{t\to t+12}$	
$PC1_t$	-0.096	-0.024	-0.056	-0.051	-0.013	-0.022	0.001	-0.005
t-stat	-(4.35)	-(1.10)	-(2.96)	-(2.53)	-(1.05)	-(1.78)	(0.08)	-(0.60)
$PC2_t$	-0.167	-0.105	-0.120	-0.058	-0.139	-0.095	-0.111	-0.079
t-stat	-(3.21)	-(2.21)	-(2.66)	-(1.56)	-(3.31)	-(2.78)	-(3.58)	-(3.03)
Macro Control	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.23	0.42	0.17	0.39	0.15	0.34	0.16	0.36
Obs	186	186	183	183	179	179	175	175

Panel B: Real Per Capita Consumption Growth

	$\triangle c_{t\to t+1}$		$\triangle c_{t\to t+4}$		$\triangle c_{t\to t+8}$		$\triangle c_{t\to t+12}$	
$PC1_t$	-0.023	-0.013	-0.015	-0.012	-0.005	-0.006	0.000	0.000
t-stat	-(4.52)	-(2.32)	-(3.44)	-(2.62)	-(1.62)	-(1.71)	(0.04)	(0.16)
$PC2_t$	-0.033	-0.023	-0.037	-0.029	-0.037	-0.031	-0.027	-0.024
t-stat	-(2.18)	-(1.51)	-(3.23)	-(2.76)	-(3.55)	-(3.33)	-(3.35)	-(3.20)
Macro Control	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.17	0.33	0.17	0.37	0.10	0.31	0.06	0.34
Obs	186	186	183	183	179	179	175	175

Panel C: Real GDP Growth

	$\triangle GDP_{t\to t+1}$		$\triangle GDP_{t\to t+4}$		$\triangle GDP_{t\to t+8}$		$\triangle GDP_{t\to t+12}$	
$PC1_t$	-0.047	-0.047	-0.027	-0.031	-0.009	-0.016	-0.001	-0.007
t-stat	-(5.60)	-(4.46)	-(3.55)	-(4.07)	-(1.41)	-(2.35)	-(0.26)	-(1.41)
$PC2_t$	-0.092	-0.087	-0.061	-0.040	-0.066	-0.048	-0.058	-0.047
t-stat	-(3.61)	-(3.18)	-(2.92)	-(1.81)	-(3.51)	-(2.78)	-(3.60)	-(3.34)
Macro Control	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.24	0.29	0.18	0.35	0.15	0.33	0.15	0.37
Obs	186	186	183	183	179	179	175	175

Panel D: Real Labor Income Growth

	$\triangle l_{t\to t+1}$		$\triangle l_{t\to t+4}$		$\triangle l_{t\to t+8}$		$\triangle l_{t\to t+12}$	
$PC1_t$	-0.039	-0.053	-0.023	-0.028	-0.006	-0.015	0.001	-0.004
t-stat	-(3.64)	-(5.02)	-(2.64)	-(3.46)	-(1.05)	-(2.46)	(0.33)	-(1.04)
$PC2_t$	-0.078	-0.076	-0.080	-0.070	-0.057	-0.049	-0.041	-0.039
t-stat	-(2.83)	-(2.66)	-(3.65)	-(3.41)	-(2.69)	-(2.64)	-(2.54)	-(2.63)
Macro Control	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.15	0.19	0.26	0.34	0.13	0.24	0.09	0.21
Obs	186	186	183	183	179	179	175	175

Table V: **Forecast the Term Structure of SPX Option Implied Volatility (VIX) Indices (Q1/1990-Q1/2015, 102 Quarters)**

This table presents ordinary least square (OLS) estimates, t-statistics (in parentheses), and adjusted OLS R-squares $\bar{R}^2$ of predictive regressions of the Chicago Board Options Exchange (CBOE) VIX index and long-term VIX indices on $PC1$ and $PC2$. The squared CBOE VIX index is the (annualized) conditional expected quadratic variation of the S&P 500 Index over the subsequent 30 days under the risk-neutral measure. The long-term VIX indices with maturities of 3, 6, and 12 months are the (annualized) conditional expected quadratic variations of the S&P 500 Index over the subsequent 3, 6, and 12 months under the risk-neutral measure. Both the CBOE VIX index and long-term VIX indices are estimated from S&P 500 European options prices in a model-free manner. $PC1$ and $PC2$ are the first and second principal components of the term structure of SPF recession probabilities (in percentage terms). The specification of the predictive regressions is as follows,

$$\log VIX_{\tau,t+h} = \alpha(\tau,h) + b1(\tau,h)PC_1(t) + b2(\tau,h)PC_2(t) + \theta(\tau,h)X_t + \epsilon_{\tau,t+h}$$

where t is measured in quarters, the forecasting horizon h is one quarter, and $\log VIX_{\tau,t+h}$ is the quarter-$t+h$ observation of the logarithm of a VIX index with maturity τ. The control variable $X(t)$ consists of the quarter-t observations of the term spread, default spread, and log returns on the S&P 500 Index in the last month of quarter-t. The sample of the CBOE VIX index is quarterly from January 1990 to April 2015 (101 quarters). The sample of the long-term VIX indices is quarterly from 1996 to August 2013 (70 quarters). t-statistics are adjusted by Newey-West standard errors with six lags. The CBOE VIX index is taken from CBOE and long-term VIX indices are taken from Travis L. Johnson's homepage .

1-Quarter Ahead VIX Indices								
	$logVIX_{1,t+1}$	$logVIX_{1,t+1}$	$logVIX_{3,t+1}$	$logVIX_{3,t+1}$	$logVIX_{6,t+1}$	$logVIX_{6,t+1}$	$logVIX_{12,t+1}$	$logVIX_{12,t+1}$
$PC1_t$	0.001	0.000	0.004	0.002	0.002	0.000	0.001	0.000
t-stat	(0.67)	-(0.18)	(1.55)	(0.90)	(0.99)	(0.33)	(0.70)	-(0.28)
$PC2_t$	0.014	0.008	0.023	0.011	0.020	0.009	0.020	0.010
t-stat	(2.14)	(2.07)	(2.69)	(2.21)	(2.73)	(2.03)	(3.05)	(2.10)
lagged Y		0.583		0.613		0.656		0.631
t-stat		(6.96)		(5.85)		(6.55)		(8.02)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
$\bar{R}^2$	0.23	0.46	0.24	0.49	0.25	0.54	0.37	0.59
Obs	101	100	70	69	70	69	70	69

Table VI: **Pricing Quarterly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios (Q1/1969-Q4/2014, 184 Quarters)**

This table presents estimates of cross-sectional regressions of average excess returns on the Fama-French 25 size- and book-to-market-sorted portfolios and the CRSP value-weighted index on their unconditional factor exposures. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is average excess return on asset i, α is the excess zero-beta rate, and ξ_i is cross-sectional pricing error of asset i. β^i_{fac} and λ_{fac} represent factor exposures of asset i and factor risk premia, respectively. CAPM is the Capital Asset Pricing Model (Mkt); I, II, and III refer to various specifications of the recession risk models. $\triangle TERM$ and $\triangle DEF$ refer to the first difference of the term spread and the default spread. Panel A reports estimated prices of risk with both Fama-MacBeth and GMM-type t-statistics, which correct the error-in-variable problem for estimated βs. Panel B reports diagnostic statistics of cross-sectional regressions, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional R-squares $\bar{R}^2$, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. p-values of the J_T statistics are shown in the row labeled "p-value". The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). The data for the three-month T-bill and the 25 Fama-French size- and book-to-market-sorted portfolios are from CRSP and Kenneth French's web site, respectively. Risk premia are reported in percentage terms per quarter.

25 Size- and B/M-sorted Portfolios					
Panel A: Prices Of Risk					
	I	**II**	**III**	**IV**	**V**
Intercept	2.99	2.75	3.10	3.47	2.96
t-FM	(2.81)	(2.57)	(2.89)	(3.06)	(3.08)
t-GMM	(3.05)	(2.52)	(2.57)	(2.13)	(2.09)
$\boldsymbol{Mkt}$	-0.92	-0.74	-1.45	-1.90	-1.43
t-FM	-(0.79)	-(0.62)	-(1.22)	-(1.51)	-(1.27)
t-GMM	(0.00)	-(0.58)	-(1.08)	-(1.10)	-(0.91)
$\triangle \boldsymbol{PC1}$		-6.21		11.69	9.27
t-FM		-(1.40)		(2.95)	(2.64)
t-GMM		-(1.21)		(1.89)	(1.85)
$\triangle \boldsymbol{PC2}$			-4.98	-7.45	-4.70
t-FM			-(2.63)	-(3.37)	-(2.45)
t-GMM			-(2.20)	-(2.28)	-(2.01)
$\triangle \boldsymbol{TERM}$					0.44
t-FM					(2.68)
t-GMM					(1.85)
$\triangle \boldsymbol{DEF}$					0.06
t-FM					(1.06)
t-GMM					(0.75)
Panel B: Test Diagnostics					
	I	**II**	**III**	**IV**	**V**
MAPE	0.49	0.45	0.27	0.25	0.26
$\bar{R}^2$	0.04	0.09	0.57	0.64	0.65
Over-identification J_T	85.95	71.13	52.12	30.83	48.05
p**-value**	0.00	0.00	0.00	0.10	0.01

Table VII: **Pricing Quarterly Excess Returns on Other Equity and Bond Portfolios (Q1/1969-Q4/2014, 184 Quarters)**

This table presents estimates of market prices of risk of the recession risk model using cross-sectional regressions of average excess returns on three sets of test assets. Panel A reports the estimates using the 25 size- and book-to-market-sorted portfolios and 5 corporate bond portfolios sorted by credit spread. Panel B reports the estimates using the 25 size and long-term reversal-sorted portfolios. Panel C reports the estimates using the 25 size- and investment-intensity-sorted portfolios. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. Factors are Mkt, $\triangle PC1$, and $\triangle PC2$. The table reports estimated market prices of risk associated with Fama-MacBeth t-statistics, as well as GMM-type t-statistics (in parentheses), and other diagnostic statistics of cross-sectional regressions, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional R-squares $\bar{R}^2$, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. The J_T statistics follow χ^2 distributions with p-values shown in parentheses. The sample is quarterly from 1976Q1 to 2010Q3 for Panel A, and from 1969Q1 to 2014Q4 for Panels B and C. The data for the 5 corporate bond portfolios are from Nozawa (2012). Other data are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

	α (t-FM) (t-GMM)	**Mkt** (t-FM) (t-GMM)	$\triangle PC1$ (t-FM) (t-GMM)	$\triangle PC2$ (t-FM) (t-GMM)	**MAPE**	$\bar{R}^2$	J_T **(p-value)**
	Panel A: 25 Size–Value Portfolios + 5 Corporate Bond Portfolios						
I	0.69	1.49			0.65	0.32	121.13 (0.00)
	(2.45)	(1.96)					
	(2.66)	(0.02)					
II	0.36	1.94	-10.12		0.63	0.35	87.06 (0.00)
	(1.48)	(2.44)	-(2.39)				
	(1.23)	(2.24)	-(2.03)				
III	0.55	1.06		-4.55	0.49	0.50	84.57 (0.00)
	(1.97)	(1.43)		-(2.64)			
	(1.78)	(1.31)		-(2.34)			
IV	0.38	1.33	-3.14	-3.66	0.47	0.49	87.29 (0.00)
	(1.57)	(1.74)	-(0.71)	-(1.93)			
	(1.33)	(1.67)	-(0.65)	-(1.80)			
	Panel B: 25 Size–Long-Term Reversal Portfolios						
I	1.20	0.85			0.40	0.04	73.10 (0.00)
	(1.50)	(0.80)					
	(1.53)	(0.00)					
II	1.22	0.85	-6.70		0.37	0.11	83.10 (0.00)
	(1.54)	(0.79)	-(1.55)				
	(1.38)	(0.74)	-(1.30)				
III	2.44	-0.67		-3.85	0.26	0.49	54.73 (0.00)
	(3.53)	-(0.70)		-(2.23)			
	(3.03)	-(0.66)		-(1.95)			
IV	2.57	-0.83	4.12	-4.45	0.25	0.48	50.66 (0.00)
	(3.33)	-(0.80)	(1.06)	-(2.31)			
	(2.65)	-(0.71)	(1.00)	-(2.07)			
	Panel C: 25 Size–Investment Portfolios						
I	2.86	-0.78			0.48	0.02	119.09 (0.00)
	(3.45)	-(0.74)					
	(3.40)	(0.00)					
II	2.92	-0.88	-8.55		0.41	0.17	85.55 (0.00)
	(3.56)	-(0.85)	-(1.96)				
	(3.01)	-(0.74)	-(1.61)				
III	3.80	-2.03		-5.53	0.26	0.59	72.23 (0.00)
	(4.66)	-(2.02)		-(2.74)			
	(3.67)	-(1.69)		-(2.16)			
IV	3.95	-2.22	7.16	-6.92	0.25	0.6	56.26 (0.00)
	(4.59)	-(2.09)	(1.83)	-(2.99)			
	(3.26)	-(1.64)	(1.33)	-(2.20)			

Table VIII: **Robustness Test: quarterly excess returns on the Fama-French 25 size- and book-to-market-sorted portfolios and the 30 industry portfolios (Q1/1969-Q3/2014, 183 Quarters)**

This table presents estimates of cross-sectional regressions using the Fama-French 25 size- and book-to-market-sorted portfolios and the CRSP value-weighted index alone, and in conjunction with the 30 Fama-French industry portfolios. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the pricing error. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. Rec refers to the recession risk model (Mkt, $\triangle PC1$, $\triangle PC2$), CC-CAY is the conditional consumption-CAPM of Lettau and Ludvigson (2001), where the consumption-wealth ratio CAY is the conditioning variable, DCAPM is the durable consumption-CAPM of Yogo (2006), including the growth rate of durable consumption $\triangle c_{dur}$ as a risk factor, U-CCAPM is the ultimate consumption risk model of Parker and Julliard (2005), with current and future 11-quarter real per capita consumption growth $\triangle c_{0\to 11}$ as the only risk factor, CCAPM is the consumption-CAPM, HL is an intertemporal CAPM of Hahn and Lee (2006), and FF3 is the Fama and French (1993) three-factor model. The table reports estimated market prices of risk, GMM-type t-statistics (in parentheses) and other diagnostic statistics, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), OLS adjusted cross-sectional R-squares $\bar{R}^2_{OLS}$, and GLS cross-sectional R-squares R^2_{GLS}, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. J_T statistics follow χ^2 distributions with p-values shown in parentheses. The sample is quarterly from 1969Q1 to 2014Q3 (183 quarters) except for the DCAPM (1969Q1 to 2001Q4) and U-CCAPM (1969Q1 to 2012Q3), constrained by data availability. Risk premia are reported in percentage terms per quarter.

Model	**Variables**				MAPE	$\bar{R}^2_{OLS}$	R^2_{GLS}	J_T (p-value)
Rec	**Const**	$\boldsymbol{Mkt}$	$\boldsymbol{\triangle PC1}$	$\boldsymbol{\triangle PC2}$				
FF25 + Mkt	3.62 (2.20)	-1.95 (-1.12)	11.9 (1.89)	-7.52 (-2.27)	0.25	0.64	0.15	30.41 (0.11)
FF25 + Mkt + 30 ind.	2.80 (3.20)	-0.98 (-0.91)	4.54 (1.48)	-2.99 (-1.99)	0.39	0.2	0.05	148.96 (0.00)
CC-CAY	**Const**	$\boldsymbol{CAY}$	$\boldsymbol{\triangle c}$	$\boldsymbol{CAY * \triangle c}$				
FF25 + Mkt	2.45 (1.48)	1.50 (1.07)	-0.11 (-0.25)	2.76 (1.94)	0.31	0.57	0.02	23.29 (0.39)
FF25 + Mkt + 30 ind.	2.13 (2.64)	0.70 (0.97)	-0.10 (-0.53)	1.09 (1.80)	0.43	0.11	0.04	131.32 (0.00)
D-CCAPM*	**Const**	$\boldsymbol{Mkt}$	$\boldsymbol{\triangle c}$	$\boldsymbol{\triangle c_{dur}}$				
FF25 + Mkt	3.33 (1.82)	-1.51 (-0.81)	0.09 (0.37)	-0.57 (-1.04)	0.35	0.56	0.05	29.59 (0.13)
FF25 + Mkt + 30 ind.	2.51 (2.69)	-0.78 (-0.67)	0.04 (0.29)	-0.09 (-0.47)	0.48	0.07	0.02	189.12 (0.00)
U-CCAPM	**Const**	$\boldsymbol{\triangle c_{0\to 11}}$						
FF25 + Mkt	0.46 (0.29)	3.83 (0.00)			0.39	0.38	0.02	32.53 (0.11)
FF25 + Mkt + 30 ind.	1.74 (2.44)	0.17 (0.00)			0.46	-0.01	0	185.35 (0.00)
CCAPM	**Const**	$\boldsymbol{\triangle c}$						
FF25 + Mkt	2.74 (3.12)	-0.16 (-0.01)			0.5	-0.01	0.01	73.53 (0.00)
FF25 + Mkt + 30 ind.	2.42 (3.78)	-0.13 (-0.03)			0.43	0.05	0.04	170.68 (0.00)
CAPM	**Const**	$\boldsymbol{Mkt}$						
FF25 + Mkt	3.17 (3.20)	-1.00 (0.00)			0.49	0.05	0.03	84.97 (0.00)
FF25 + Mkt + 30 ind.	2.46 (3.20)	-0.50 (0.00)			0.44	0.02	0.02	188.29 (0.00)
HL	**Const**	$\boldsymbol{Mkt}$	$\boldsymbol{\triangle TERM}$	$\boldsymbol{\triangle DEF}$				
FF25 + Mkt	2.30 (1.73)	-0.79 (-0.53)	0.58 (2.52)	0.01 (0.11)	0.28	0.64	0.1	42.97 (0.00)
FF25 + Mkt + 30 ind.	2.06 (2.49)	-0.38 (-0.36)	0.25 (1.90)	0.02 (0.58)	0.37	0.13	0.03	162.33 (0.00)
FF3	**Const**	$\boldsymbol{Mkt}$	$\boldsymbol{SMB}$	$\boldsymbol{HML}$				
FF25 + Mkt	3.40 (3.14)	-1.81 (-1.41)	0.33 (0.77)	1.18 (2.43)	0.24	0.63	0.14	70.27 (0.00)
FF25 + Mkt + 30 ind.	2.93 (-1.24)	-1.26 (0.60)	0.26 (0.60)	0.83 (1.67)	0.36	0.28	0.07	172.41 (0.00)

Table IX: **GMM SDF Tests and Model Comparison Tests (Q1/1969-Q3/2014, 183 Quarters)**

This table presents GMM SDF tests and Hansen-Jagannathan (HJ) distances for competing macro-factor models. In Panel A, test assets are the 25 Fama-French size- and book-to-market-sorted portfolios, the 30 Fama-French industry portfolios, and the CRSP value-weighted index. The first block in Panel A reports GMM SDF tests, which examine whether factors in other models drive out $\triangle PC2$. The test statistics are Wald statistics based on the efficient GMM outlined in "Model Comparison" in Section 4.3. CC-CAY is the conditional consumption-CAPM by Lettau and Ludvigson (2001), where the consumption-wealth ratio CAY is the conditioning variable, DCAPM is the durable consumption-CAPM by Yogo (2006), U-CCAPM is the ultimate consumption-CAPM of Parker and Julliard (2005), CCAPM is the static consumption-CAPM, HL is an intertemporal CAPM of Hahn and Lee (2006), and FF3 is the Fama-French three-factor model. The second block reports efficient GMM Wald statistics, which examine, in the presence of three risk factors in *Rec*, whether (non-overlapping) factors in other models are driven out. Panel B reports squared HJ distances of competing models and difference in squared HJ distance between the models and the recession risk model ($\delta^2_{model} - \delta^2_{rec}$), using gross returns on the 25 size and B/M portfolios alone, or in conjunction with 30 industry portfolios. The sample is quarterly from 1969Q1 to 2014Q3 (183 quarters) except for DCAPM (1969Q1 to 2001Q4) and U-CCAPM (1969Q1 to 2012Q3), constrained by data availability.

Panel A: GMM SDF Test: $M = 1 - b'[f - \mu_f]$						
H0: $b_{\triangle PC2} = 0$	**CCAPM**	**CC-CAY**	**D-CCAPM***	**U-CCAPM**	**HL**	**FF3**
Wald χ^2	4.713	7.676	9.970	5.768	6.224	9.314
p-value	(0.03)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)
H0: Rec drives out other factors, $b_{other}=0$						
Wald χ^2	0.174	45.700	26.211	2.665	16.904	22.600
p-value	(0.68)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)
Panel B: Hansen-Jagannathan Distances						
FF25 + Mkt	**CCAPM**	**CC-CAY**	**D-CCAPM***	**U-CCAPM**	**HL**	**FF3**
δ^2_{model}	0.447	0.442	0.567	0.457	0.400	0.378
$\delta^2_{model} - \delta^2_{rec}$	0.072	0.067	0.099	0.089	0.025	0.002
FF25 + 30 Ind + Mkt						
δ^2_{model}	0.934	0.941	1.414	0.981	0.937	0.897
$\delta^2_{model} - \delta^2_{rec}$	0.015	0.021	0.033	0.073	0.017	-0.023

Table X: **Time Series Regressions of Quarterly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios and the 10 Industry Portfolios on the Recession Risk Model (Q1/1969-Q4/2014, 184 Quarters)**

This table shows time series regressions of quarterly excess returns of the 25 Fama-French size- and book-to-market-sorted portfolios on the recession risk model.

$$R^e_{i,t} = a_i + \beta^i_{Mkt} Mkt_t + \beta^i_{\triangle PC1} \triangle PC1_t + \beta^i_{\triangle PC2} \triangle PC2_t + \epsilon^i_t$$

where i indexes assets, Mkt_t, $\triangle PC1_t$ and $\triangle PC2_t$ denote excess return on the CRSP value-weighted index, and the innovations to $PC1$ and $PC2$, respectively. $PC1$ and $PC2$ are the first (level) and the second principal components (slope) of the term structure of SPF recession probabilities (in percentage terms). The innovations to $PC1$ and $PC2$ are estimated by a first-order VAR of $PC1$ and $PC2$ over the entire sample. β^i_{Mkt}, $\beta^i_{\triangle PC1}$ and $\beta^i_{\triangle PC2}$ are unconditional factor exposures of the excess return of asset i, $R^e_{i,t}$, on Mkt_t, $\triangle PC1_t$ and $\triangle PC2_t$. $E[R^e]$ refers to average excess return (actual return in excess of return on the 3 month T-bill) and R^2 is the unadjusted R-squares. t-statistics of factor exposures are adjusted by Newey-West standard errors with 1 lag. χ^2_{25} refers to a large sample likelihood-ratio test for the null hypothesis that all 25 factor exposures of a risk factor are jointly zero. The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). The data for the three-month T-bill and the 25 Fama-French size- and book-to-market-sorted portfolios are from CRSP and Kenneth French's web site, respectively. Returns and risk premia are reported in percentage terms per quarter.

	Book-to-Market Equity					Book-to-Market Equity					
	Low	2	3	4	High	Low	2	3	4	High	
	Panel A $E[R^e]$ (%)					Panel B Time Series R^2					
Small	0.29	2.06	2.17	2.72	3.10	0.74	0.75	0.73	0.71	0.68	
2	1.21	1.98	2.46	2.57	2.74	0.82	0.80	0.80	0.74	0.69	
3	1.36	2.14	2.12	2.37	3.00	0.85	0.86	0.80	0.76	0.66	
4	1.79	1.64	2.04	2.24	2.36	0.87	0.86	0.83	0.80	0.72	
Big	1.34	1.66	1.37	1.52	1.76	0.89	0.89	0.80	0.76	0.66	
	Panel C β_{Mkt}					Panel D $t(\beta_{Mkt})$					χ^2_{25}
Small	1.56	1.30	1.12	1.03	1.13	20.22	18.24	16.88	16.43	14.56	> 100
2	1.49	1.22	1.07	1.01	1.07	22.26	20.01	18.52	17.03	14.50	p-value
3	1.40	1.15	1.00	0.96	0.99	26.99	24.63	17.19	16.84	13.53	0
4	1.29	1.10	0.99	0.95	1.02	30.25	23.46	20.29	18.45	13.85	
Big	1.01	0.91	0.81	0.79	0.83	38.09	32.27	23.44	18.00	15.05	
	Panel E β_{PC1}					Panel F $t(\beta_{PC1})$					χ^2_{25}
Small	-0.03	-0.04	-0.07	-0.06	-0.09	-0.58	-1.07	-2.02	-1.99	-2.46	81.41
2	0.03	0.00	-0.03	-0.01	-0.04	0.93	-0.01	-1.00	-0.32	-1.11	p-value
3	0.05	0.00	0.00	-0.02	0.02	1.86	0.11	-0.17	-0.74	0.60	0
4	0.04	0.01	-0.02	0.00	-0.03	2.32	0.90	-0.93	0.11	-0.98	
Big	0.02	-0.01	-0.03	-0.02	-0.02	1.65	-0.48	-1.61	-1.11	-0.50	
	Panel G β_{PC2}					Panel H $t(\beta_{PC2})$					χ^2_{25}
Small	-0.14	-0.21	-0.20	-0.24	-0.33	-1.18	-2.20	-2.10	-2.92	-3.53	93.40
2	-0.04	-0.11	-0.13	-0.15	-0.22	-0.57	-1.31	-2.11	-2.60	-2.80	p-value
3	0.02	-0.09	-0.09	-0.15	-0.12	0.27	-2.04	-1.89	-3.53	-1.63	0
4	0.06	-0.02	-0.11	-0.13	-0.09	1.54	-0.63	-2.66	-3.43	-1.36	
Big	0.07	0.02	0.03	-0.05	-0.09	2.15	0.68	0.82	-1.33	-1.45	

Table XI: **Forecasting Cumulative Profitability Changes of Book-to-Market-Sorted Portfolios (1969-2013, 45 Years)**

This table reports ordinary least square (OLS) estimates, t-statistics (in parentheses), and adjusted OLS $\bar{R}^2 s$ of predictive regressions of annualized cumulative changes in the portfolio-level profitability of five book-to-market-sorted portfolios on $PC1$ and $PC2$. $PC1$ and $PC2$ are the first (Level) and second (Slope) principal components of the term structure of SPF recession probabilities (in percentage terms). Firm-level profitability is measured by ROA, defined as current year operating income before depreciation (Compustat item: OIBDP) divided by average total assets (Compustat item: AT) of the current year and previous year. Portfolio-level profitability is the value-weighted ROA of individual firms within each portfolio. The specification of predictive regressions is as follows,

$$\overline{\triangle \text{Profit}}^{i}_{t-1\to t+h-1} = \alpha^i(h) + b1^i(h)PC_1(t) + b2^i(h)PC_2(t) + \epsilon^i_{t,h}$$

where time t is measured annually, $\overline{\triangle \text{Profit}}^{i}_{t-1\to t+h-1} \equiv \frac{100}{h}(\text{Profit}^i_{t+h-1} - \text{Profit}^i_{t-1})$ is annualized cumulative changes in the profitability of portfolio i from year $t-1$ to year $t+h-1$, and the forecasting horizon h takes the values 2, 3, and 4. The five book-to-market-sorted portfolios are constructed in the manner of Fama and French (1992). L, M, and H denote three different portfolios, consisting of stocks in the first, third, and fifth book-to-market quintile. t-statistics (in parentheses) are adjusted using the Hodrick (1992) standard errors. The data is annually from 1969 to 2013, 45 years in total. Firm-level accounting data are from Compustat.

Forecasting Annualized Cumulative Changes in Portfolio-Level Profitability									
	$\overline{\triangle \text{Profit}}_{t-1\to t+1}$			$\overline{\triangle \text{Profit}}_{t-1\to t+2}$			$\overline{\triangle \text{Profit}}_{t-1\to t+3}$		
	L	M	H	L	M	H	L	M	H
$PC1_t$	-0.010	-0.021	-0.009	-0.004	-0.016	-0.004	-0.003	-0.011	0.000
t-stat	-(2.31)	-(5.82)	-(2.30)	-(1.20)	-(4.73)	-(1.23)	-(1.27)	-(3.86)	-(0.20)
$PC2_t$	-0.011	-0.014	-0.021	-0.017	-0.027	-0.029	-0.017	-0.026	-0.022
t-stat	-(1.02)	-(1.96)	-(1.66)	-(1.87)	-(3.80)	-(2.75)	-(2.54)	-(3.73)	-(2.79)
$\bar{R}^2$	0.05	0.23	0.18	0.02	0.38	0.29	0.06	0.35	0.26
Obs	45	45	45	44	44	44	43	43	43

Table XII: **Quarterly Excess Returns on Factor Mimicking Portfolios (Q1/1969-Q4/2014, 184 Quarters)**

This table presents summary statistics of factor mimicking portfolios (FMPs) of $\triangle PC1$ and $\triangle PC2$ ($\triangle PC1$ **FMP** and $\triangle PC2$ **FMP**, respectively). $PC1$ and $PC2$ are the first and second principal components of the term structure of SPF recession probability forecasts. $\triangle PC1_t$ and $\triangle PC2_t$ are the innovations to $PC1$ and $PC2$, respectively, estimated by a VAR(1) model of $PC1$ and $PC2$ using the whole sample. The two FMPs are created by projecting $\triangle PC1$ and $\triangle PC2$ into a space of basis assets as follows,

$$y_t = a + b^{'}X_t + \epsilon_t,\ y_t \in \{\triangle PC1_t, \triangle PC2_t\}$$

where b is estimated by ordinary least squares and the FMPs are given by $b^{'}X_t$. The space of basis assets is $X_t = [BL, BM, BH, SL, SM, SH, b1, b4, b5, corpr]$ where the first six variables denote excess returns on the six Fama-French size- and book-to-market-sorted portfolios. $b1$, $b4$, and $b5$ refer to excess returns on the three Fama bond portfolios sorted by maturity, which comprise U.S. T-bills or T-bonds with maturities of 0-1, 3-4, and 4-5 years, respectively, and *corpr* is the excess return on the Ibboston long-term corporate bond portfolio, which comprises investment-grade corporate bonds with maturity of greater than 10 years. Panel A reports the quarterly means, standard deviations and annualized Sharpe ratios (SR) of the two FMPs and the Fama-French three factors. Panel B reports the correlation between the two FMPs and the Fama-French three factors. Panel C reports the time series regressions of $\triangle PC2$ **FMP** on the CAPM and the Fama-French three factors. Panel D reports GRS F-statistics with associated p-values for four models, CAPM, the Fama-French three-factor model, market with $\triangle PC2$ **FMP**, denoted MKT+$\triangle PC2$ FMP, and market with $\triangle PC1$ **FMP** and $\triangle PC2$ **FMP**, denoted "Rec FMP". The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). Returns and risk premia are reported in percentage terms per quarter.

Panel A: Sample Moments

	Mean	t-value	Std	Annualized SR
$\triangle PC1$ **FMP**	0.29	(0.55)	7.15	0.08
$\triangle PC2$ **FMP**	-0.77	-(4.30)	2.58	-0.59
Mkt	1.54	(2.28)	8.92	0.35
SMB	0.53	(1.32)	5.62	0.19
HML	1.06	(2.24)	6.03	0.35

Panel B: Correlation Matrix

	$\triangle PC1$ **FMP**	Mkt	SMB	HML
$\triangle PC2$ **FMP**	0.27	-0.41	-0.67	-0.29
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Mkt	-0.48		0.46	-0.34
p-value	(0.00)		(0.00)	(0.00)
SMB	-0.26			-0.11
p-value	(0.00)			(0.13)
HML	-0.04			
p-value	(0.57)			

Panel C: CAPM and FF3 α

$\triangle PC2$ **FMP**	α	β_{Mkt}	β_{SMB}	β_{HML}	$\bar{R}^2$
CAPM	-0.59	-0.12			0.16
	-(3.42)	-(5.48)			
FF3	-0.29	-0.08	-0.27	-0.20	0.64
	-(2.34)	-(5.11)	-(12.58)	-(9.30)	

Panel D: GRS F-Tests

FF25	CAPM	FF3	MKT+$\triangle PC2$ FMP	Rec FMP
GRS	3.80	3.19	3.22	3.21
p-value	0.00	0.00	0.00	0.00

Table XIII: **Pricing Monthly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios and the 10 Industry Portfolios (7/1963-12/2014, 618 Months)**

This table presents cross-sectional regressions of average excess returns on the Fama-French 25 size- and book-to-market-sorted portfolios and the 10 industry portfolios on their unconditional factor exposures. The sample is monthly from July 1963 to December 2014, 618 months in total. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error of asset i. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. CAPM is the Capital Asset Pricing Model, FF3 denotes the Fama-French three-factor model, Rec FMP stands for the factor mimicking portfolios of the recession risk model (Mkt, $\triangle PC1$ FMP, $\triangle PC2$ FMP), and MKT+$\triangle PC2$ FMP is a two-factor specification of the recession risk model. See Table XII for the description of the factor mimicking portfolios. Panel A reports estimated prices of risk with Fama-MacBeth and GMM-type t-statistics that correct the error-in-variable problem for estimated βs. Panel B displays diagnostic statistics, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), adjusted OLS and GLS cross-sectional R-squares, Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i, and GRS F-statistics for the joint significance of the intercepts in time series regressions. The J_T statistics follow χ^2 distributions with p-values shown in the row labeled "J_T p-value". "GRS p-value" are the p-values of the GRS statistics. Risk premia are reported in percentage terms per quarter.

Panel A: Prices Of Risk

	CAPM	**FF3**	**Rec FMP**	**MKT+$\triangle PC2$ FMP**
Intercept	2.15	2.56	2.91	3.14
t-FM	(2.56)	(4.24)	(4.33)	(3.64)
t-GMM	(2.53)	(4.05)	(4.24)	(3.71)
Mkt	-0.10	-0.92	-1.32	-1.52
t-FM	-(0.09)	-(1.12)	-(1.47)	-(1.46)
t-GMM	(0.00)	-(1.08)	-(1.47)	-(1.49)
SMB		0.57		
t-FM		(1.41)		
t-GMM		(1.44)		
HML		0.92		
t-FM		(2.29)		
t-GMM		(2.21)		
$\triangle PC1$ FMP			-0.24	
t-FM			-(0.25)	
t-GMM			-(0.24)	
$\triangle PC2$ FMP			-0.58	-0.59
t-FM			-(2.24)	-(2.30)
t-GMM			-(2.40)	-(2.43)

Panel B: Test Diagnostics

	CAPM	**FF3**	**Rec FMP**	**MKT+$\triangle PC2$ FMP**
MAPE	0.50	0.30	0.27	0.27
$\bar{R}^2_{OLS}$	-0.03	0.51	0.57	0.57
R^2_{GLS}	0.06	0.19	0.24	0.23
Over-identification J_T	126.73	112.75	104.80	106.20
J_T p-value	0.00	0.00	0.00	0.00
GRS	4.71	4.03	4.37	4.20
GRS p-value	0.00	0.00	0.00	0.00

Table XIV: **Pricing Monthly Excess Returns on the SPX Index Options Portfolios and the Fama-French 25 Size- and Book-to-market-sorted Portfolios (4/1986-1/2012, 310 Months)**

This table presents cross-sectional regressions of average excess returns on the 18 S&P 500 Index option portfolios and the 25 size- and book-to-market-sorted portfolios on their unconditional factor exposures. The 18 option portfolios comprise an equal number of European call and put options with maturities of 30 days, 60 days, and 90 days and spot-to-strike ratios of 0.9, 1, and 1.1, respectively. The sample is monthly from April 1986 to January 2012, 310 months in total. Each model is estimated via a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. DCAPM is downside CAPM (Mkt, $MktDR$), FF3 denotes the Fama-French three-factor model (Mkt, SMB, HML), and Rec FMP stands for the factor mimicking portfolios of the recession risk model (Mkt, $\triangle PC1$ FMP, $\triangle PC2$ FMP). See Table XII for the description of the factor mimicking portfolio. Panel A reports estimated prices of risk with Fama-MacBeth and GMM-type t-statistics, which correct the error-in-variable problem for estimated βs. Panel B displays diagnostic statistics, including mean absolute pricing errors (MAPEs, defined as $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional OLS $\bar{R}^2$ and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. The J_T statistics follow χ^2 distributions with degree of freedom (p-value) shown in the row labeled "Degree of freedom" (J_T p-value). The data for the S&P 500 Index option portfolios are from Constantinides, Jackwerth and Savov (2013). The data for the one-month T-bill and the 25 size- and book-to-market-sorted portfolios are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

	Panel A: Prices Of Risk					
	SPX Options			SPX Options + Equities		
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
Intercept				2.00	**-3.00**	**-4.18**
t-FM				(1.50)	-(2.47)	-(3.11)
t-GMM				-	-(2.33)	-(2.84)
Mkt	**2.11**	**1.65**	**2.70**	-0.50	**4.53**	**5.78**
t-FM	(2.48)	(2.00)	(3.21)	-(0.30)	(2.93)	(3.44)
t-GMM	-	(1.85)	(3.14)	-	(2.88)	(3.32)
MktDR	**4.63**			**4.19**		
t-FM	(4.61)			(4.41)		
t-GMM	-			-		
SMB			**8.25**			0.23
t-FM			(5.74)			(0.39)
t-GMM			(4.74)			(0.42)
HML			-1.24			0.95
t-FM			-(0.36)			(1.45)
t-GMM			-(0.28)			(1.44)
$\triangle PC1$ **FMP**		-0.12			**-3.86**	
t-FM		-(0.05)			-(3.58)	
t-GMM		-(0.04)			-(3.33)	
$\triangle PC2$ **FMP**		**-2.83**			**-0.81**	
t-FM		-(4.35)			-(2.33)	
t-GMM		-(3.63)			-(2.46)	

	Panel B: Test Diagnostics					
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
MAPE	0.38	0.32	0.38	0.50	0.56	0.55
$\bar{R}^2$	0.88	0.89	0.85	0.63	0.49	0.50
Over-identification J_T	169.90	102.35	92.71	285.20	230.30	226.70
Degree of freedom	17	16	16	41	40	40
J_T p-value	0.00	0.00	0.00	0.00	0.00	0.00

Table XV: **Pricing Monthly Excess Returns on the Five Currency Portfolios and the Fama-French 25 Size- and Book-to-market-sorted Portfolios (1/1974-3/2010, 435 Months)**

This table presents cross-sectional regressions of average excess returns on the 5 currency portfolios and the 25 size- and book-to-market-sorted portfolios on their unconditional factor exposures. The 5 currency portfolios are nominal-interest-rate-sorted currency portfolios, which comprise currencies of developed countries. Each currency portfolio is a zero-cost portfolio that takes long positions in currencies of developed countries other than the U.S., while funding the positions by borrowing U.S. dollars. The sample is monthly from January 1974 to March 2010, 435 months in total. Each model is estimated via a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$, where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error of asset i. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. DCAPM is the downside CAPM (Mkt, $MktDR$), FF3 denotes the Fama-French three-factor model (Mkt, SMB, HML), and Rec FMP stands for the factor mimicking portfolio of the macroeconomic recession risk model (Mkt, $\triangle PC1$ FMP, $\triangle PC2$ FMP). See Table XII for the description of the factor mimicking portfolio. Panel A reports estimated prices of risk with Fama-MacBeth and GMM-type t-statistics that correct the error-in-variable problem for estimated βs. Panel B displays diagnostic statistics, including mean absolute pricing errors (MAPEs, defined as $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional $\bar{R}^2$, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. The J_T statistics follow χ^2 distributions with degree of freedom (p-value) shown in the row labeled "Degree of freedom" (J_T p-value). The data for the 5 currency portfolios are from Lettau, Maggiori, and Weber (2014). The data for the one-month T-bill and the 25 size- and book-to-market-sorted portfolios are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

	Panel A: Prices Of Risk					
	Currency			Currency + Equities		
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
Intercept				0.44	**0.91**	0.42
t-FM				(1.14)	(2.26)	(1.13)
t-GMM				-	(2.15)	(1.13)
Mkt	**1.55**	**1.59**	**1.60**	0.98	0.45	1.04
t-FM	(2.21)	(2.25)	(2.26)	(1.17)	(0.55)	(1.31)
t-GMM	-	(2.22)	(2.23)	-	(0.54)	(1.29)
MktDR	**7.38**			**4.81**		
t-FM	(2.32)			(3.90)		
t-GMM	-			-		
SMB			-4.54			0.78
t-FM			-(0.62)			(1.64)
t-GMM			-(0.56)			(1.75)
HML			3.62			**1.45**
t-FM			(1.30)			(2.78)
t-GMM			(1.15)			(2.75)
$\triangle PC1$ **FMP**		2.64			**-3.91**	
t-FM		(0.94)			-(2.47)	
t-GMM		(0.76)			-(2.26)	
$\triangle PC2$ **FMP**		**-3.07**			**-0.85**	
t-FM		-(3.14)			-(2.80)	
t-GMM		-(2.48)			-(2.93)	

	Panel B: Test Diagnostics					
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
MAPE	0.20	0.33	0.40	0.40	0.32	0.34
$\bar{R}^2$	0.85	0.60	0.50	0.70	0.81	0.79
Over-identification J_T	9.79	7.65	10.97	111.90	85.92	106.02
Degree of freedom	4	3	3	28	27	27
J_T p-value	0.04	0.05	0.01	0.00	0.00	0.00

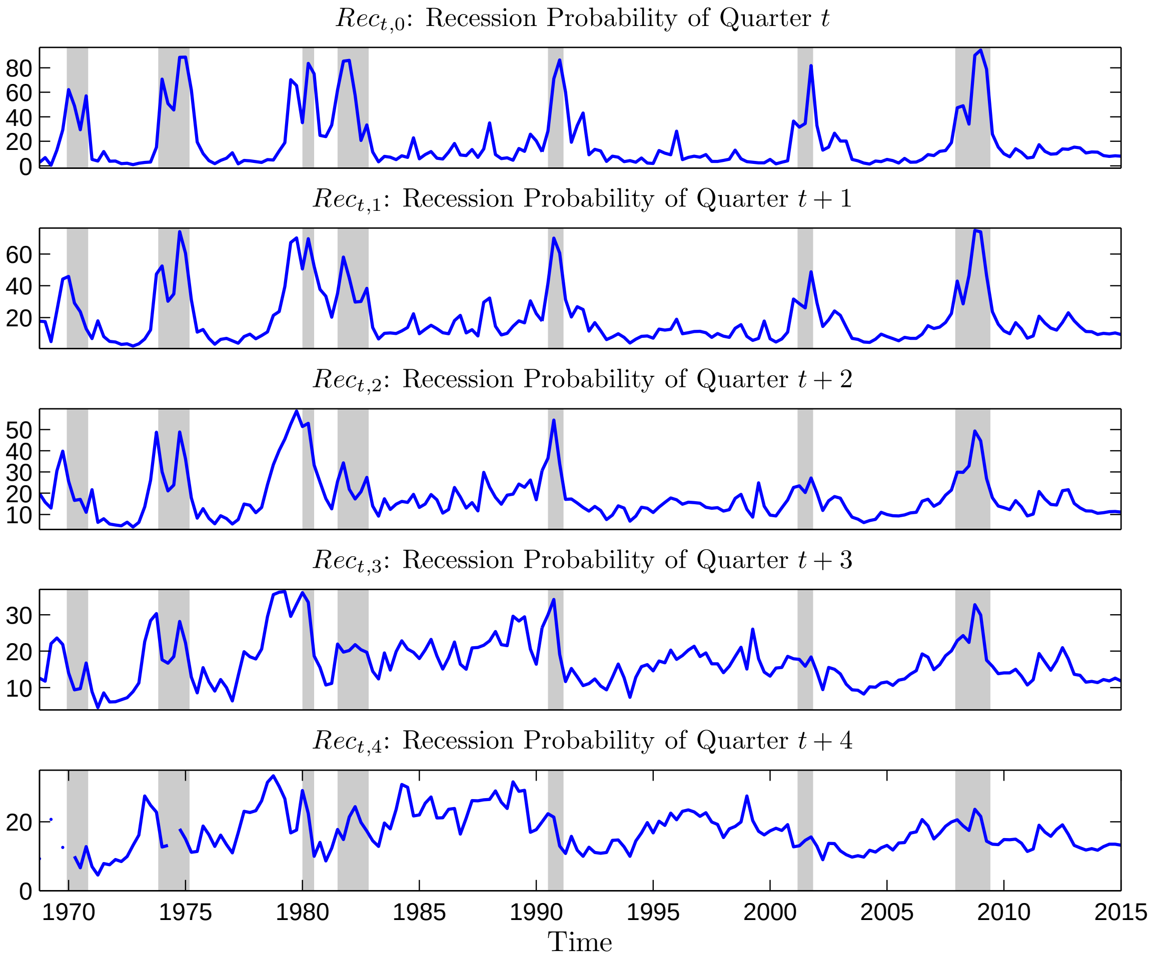

Figure 1: **SPF Recession Probabilities (%)**

Figure 1 plots the time series of recession probability forecasts from the Survey of Professional Forecasters (SPF) database. A recession probability forecast for quarter-$t+i$ made at quarter-t, denoted $Rec_{t,i}$, is the probability of a decline in U.S. real gross domestic product (GDP) in quarter-$t+i$. Mathematically, $Rec_{t,i}$ is defined as $Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1}), i \in \{0, 1, ..., 4\}$ where time t is measured in quarters and GDP_{t+i} refers to the level of real GDP in quarter-$t+i$. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

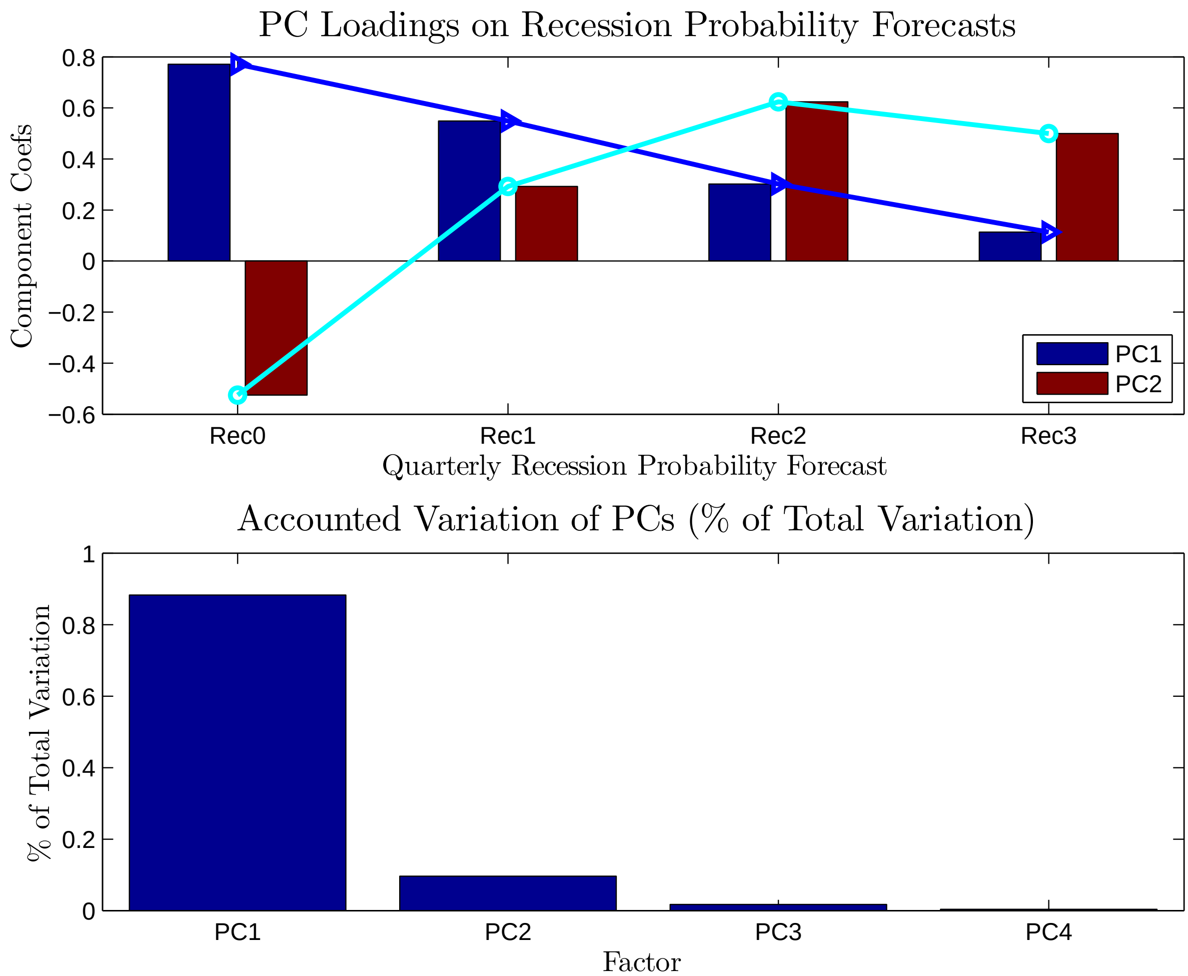

Figure 2: **Principal Components of the Term Structure of SPF Recession Probabilities**

Panel A of Figure 2 plots the loadings of the first two principal components of the term structure of recession probabilities on each individual recession probability. Panel B displays the proportion of the variation of the term structure accounted for by each principal component. A recession probability forecast of quarter-$t+i$ made at quarter-t is denoted $Rec_{t,i}$ and is the probability of a decline in U.S. real gross domestic product (GDP) in quarter-$t+i$. Mathematically, $Rec_{t,i}$ is defined as $Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1}), i \in \{0, 1, ..., 3\}$ where the time t is measured in quarters and GDP_{t+i} refers to the level of real GDP in quarter-$t+i$. The data are from the Survey of Professional Forecasters (SPF) database. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

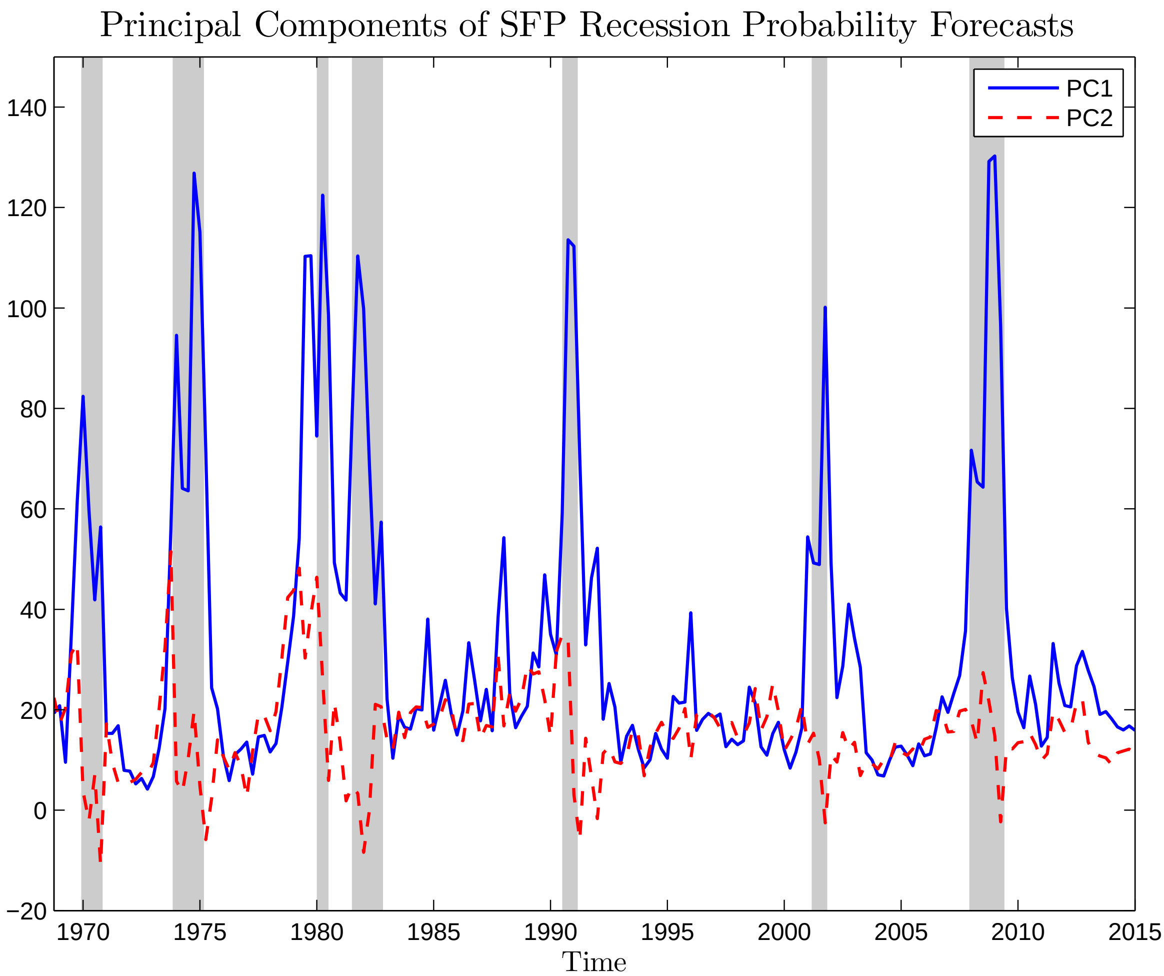

Figure 3: **Dynamics of Principal Components of the SPF Recession Probabilities**

Figure 3 plots the time series of the first ($PC1$) and the second ($PC2$) principal components of the term structure of recession probabilities. The recession probability forecasts are the probabilities of a decline in U.S. real gross domestic product (GDP) in the current quarter and the next three quarters. The solid blue line is the time series of $PC1$ and the dashed red line is the time series of $PC2$. The data on recession probabilities are from the Survey of Professional Forecasters (SPF) database. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

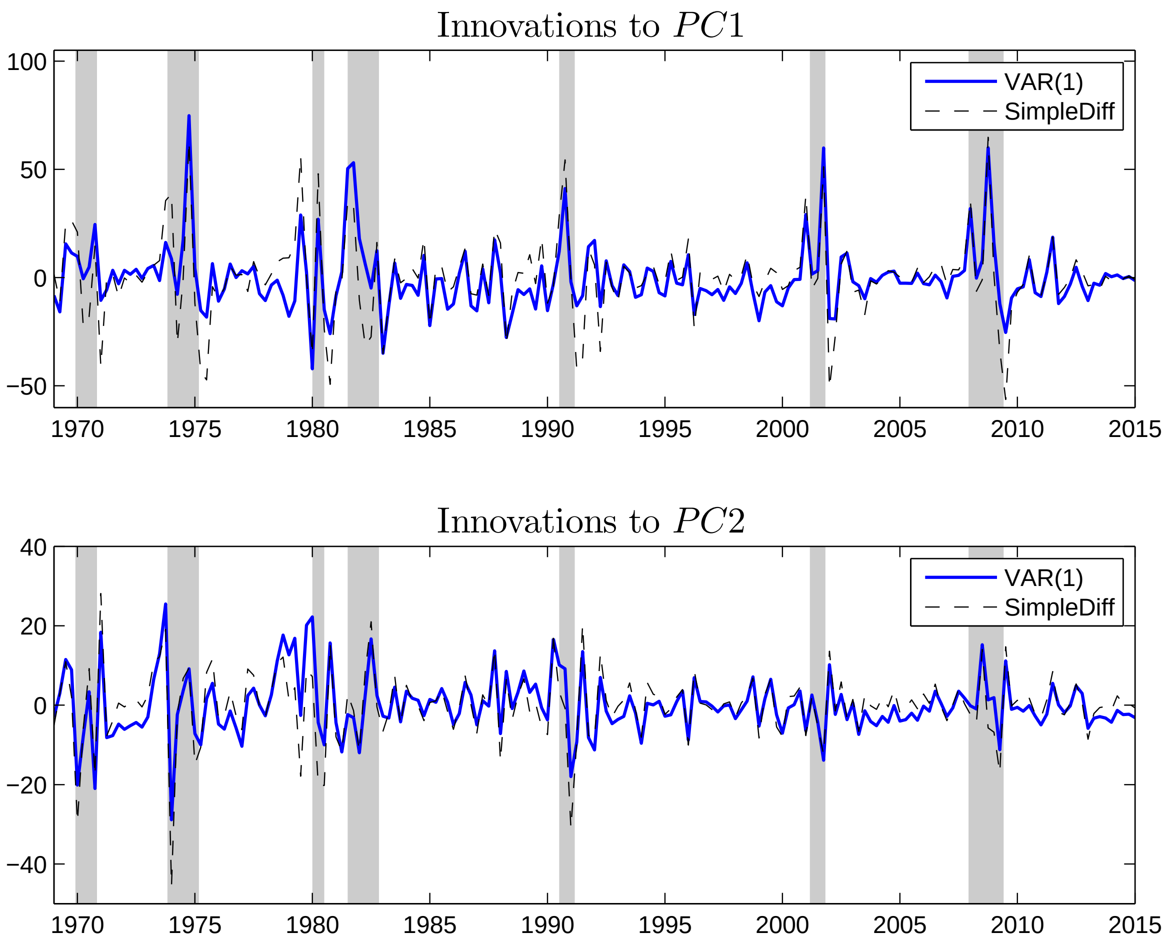

Figure 4: **Innovations to the Principal Components of the SPF Recession Probabilities**

Figure 4 plots the innovations to the first ($PC1$) and the second ($PC2$) principal components of the term structure of recession probabilities. The solid blue line is the innovation estimated by a first-order VAR and the dashed black line is the innovation estimated by simple first difference. The data of recession probabilities are from the Survey of Professional Forecasters (SPF) database. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

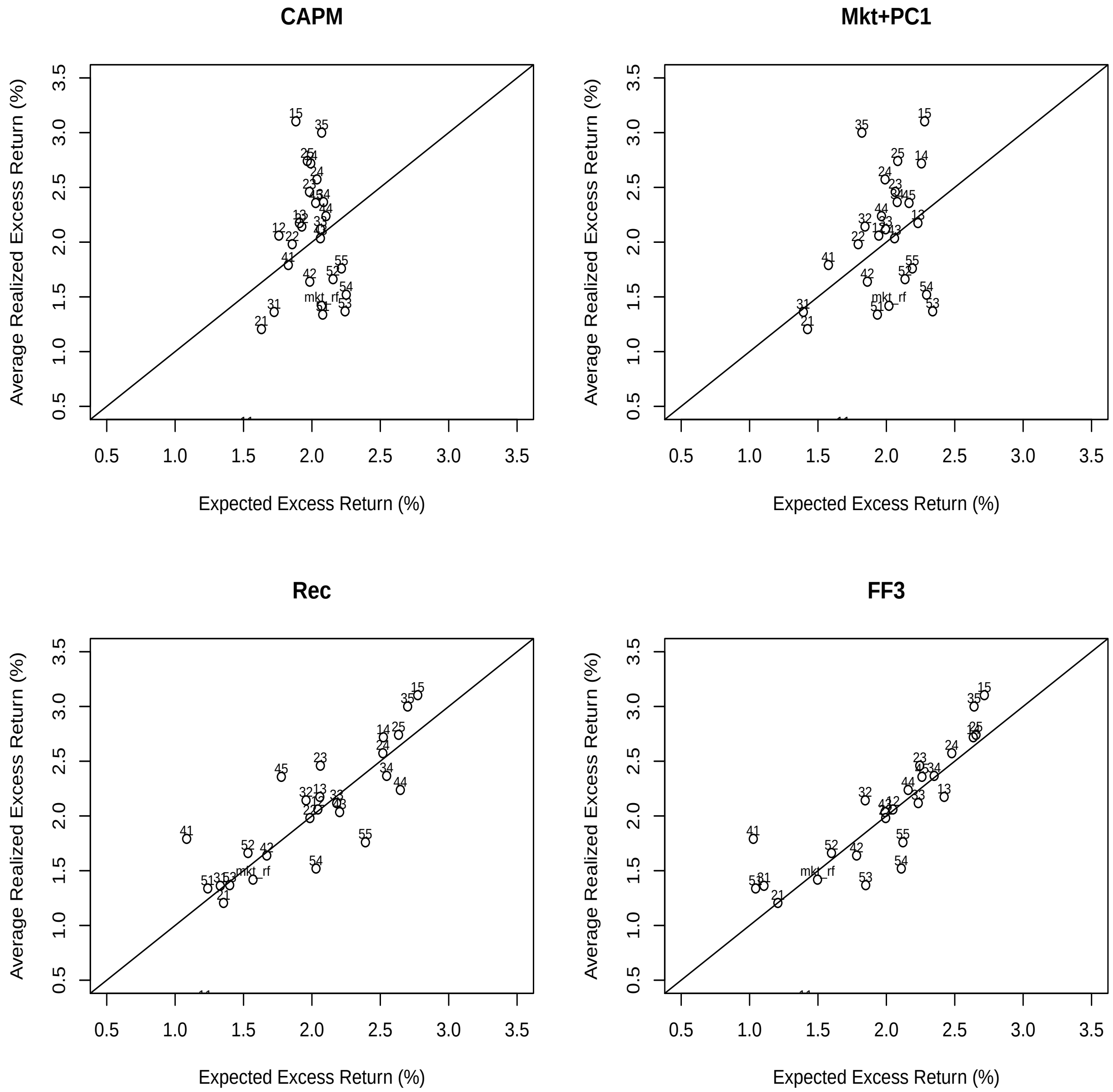

Figure 5: **Pricing Quarterly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios, Q1/1969-Q4/2014, 184 Quarters**

Figure 5 plots average quarterly excess returns on 26 equity portfolios (the 25 Fama-French size- and book-to-market-sorted portfolios (labeled 11-55), and the CRSP value-weighted index (labeled Mkt_rf)) against the mean excess returns predicted by four models. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \alpha\mathbf{1}+\beta'_{fac}\lambda_{fac}+\xi$ where $E_T[R_t^e]$ is the vector of the average excess returns, α is the excess zero-beta rate, and ξ is the vector of pricing errors. The predicted mean excess returns are $\alpha\mathbf{1} + \beta'_{fac}\lambda_{fac}$. CAPM stands for the Capital Asset Pricing Model, FF3 denotes the Fama-French three-factor model, Rec refers to the recession risk model, and Mkt+PC1 is a two-factor model with the market and the innovation to $PC1$. The sample is quarterly from 1969Q1 to 2014Q4.

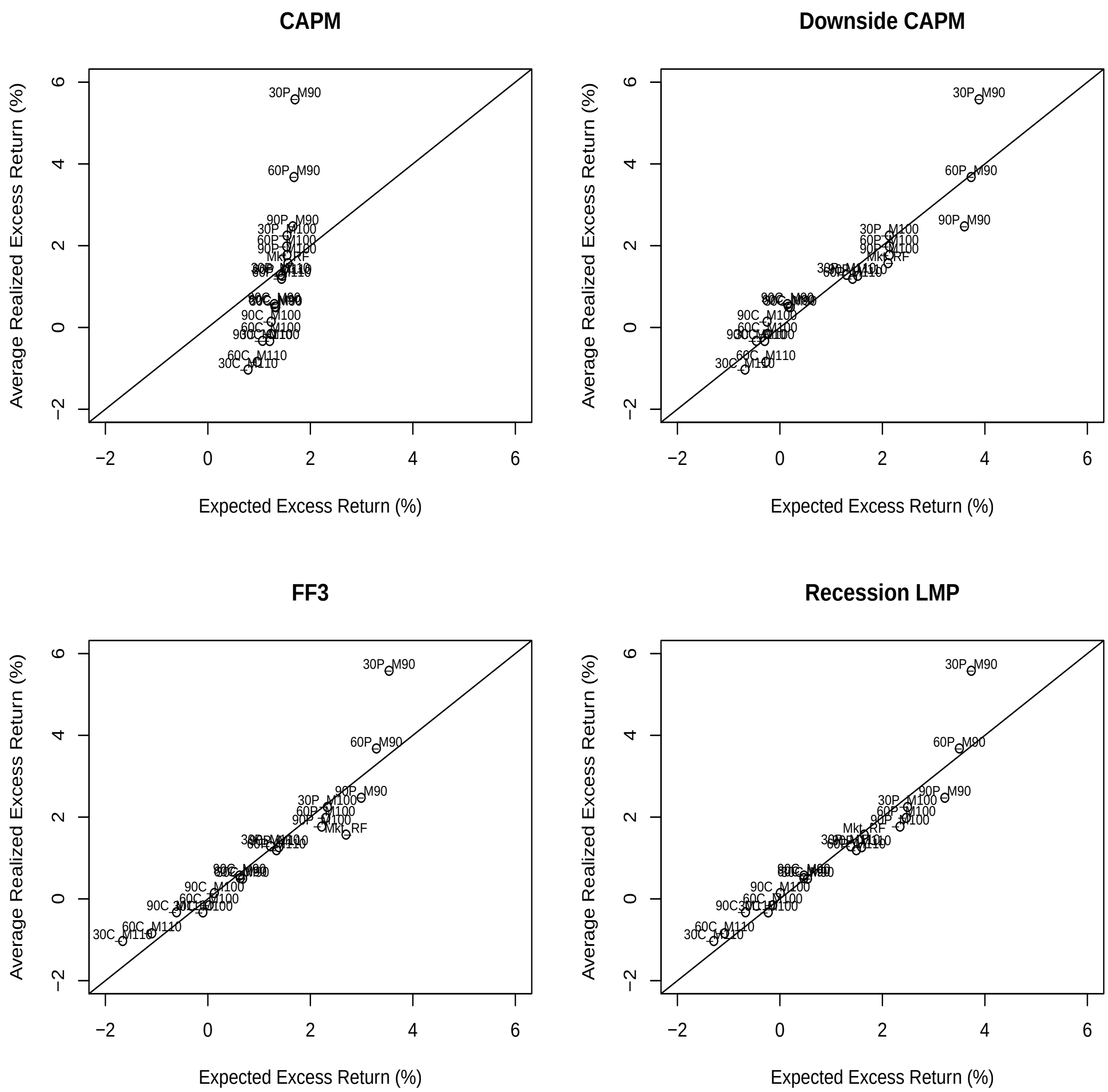

Figure 6: **Pricing Monthly Excess Returns on the SPX Index Options Portfolios, 4/1986-1/2012, 310 Months**

Figure 6 plots average realized excess returns on the 18 S&P 500 index option portfolios and the CRSP value-weighted index (labeled Mkt_rf) against the mean excess returns predicted by four models. Each option portfolio is labeled in a way that the first two digits refer to maturity, C or P stand for call or put, respectively, and the last two digits denote moneyness. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of average excess returns, and ξ is the vector of pricing errors. The predicted mean excess returns are $\beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XII for the factor mimicking portfolios.). The sample is monthly from 4/1986-1/2012 but returns are expressed in percentage terms per quarter.

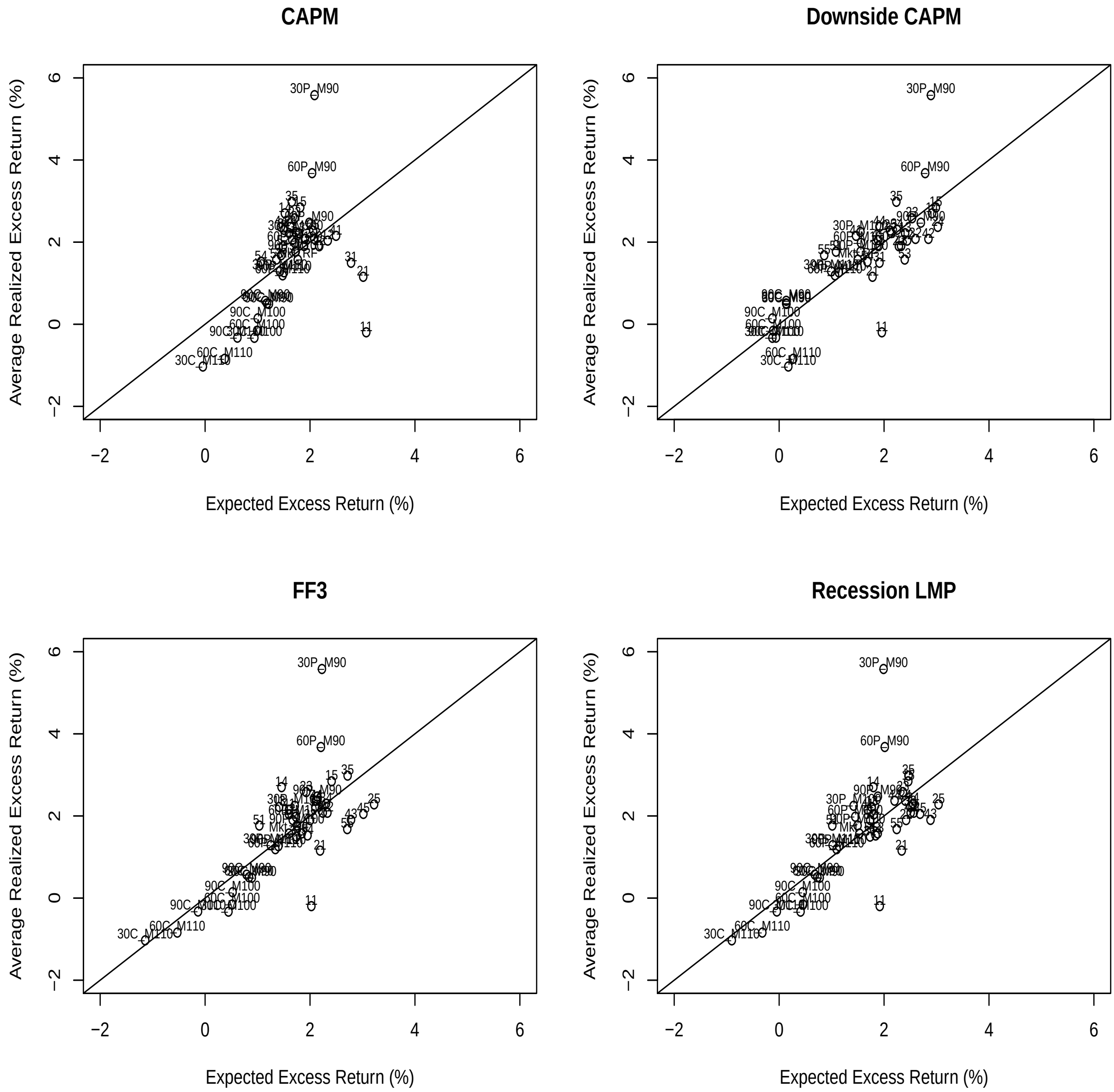

Figure 7: **Pricing Monthly Excess Returns on the SPX Index Options and the Fama-French 25 Size- and Book-to-Market-sorted Portfolios, 4/1986-1/2012, 310 Months**

Figure 7 plots average realized excess returns on the 18 S&P 500 Index option portfolios, the 25 Fama-French size- and book-to-market-sorted portfolios (labeled 11-55) and the CRSP value-weighted index (labeled Mkt_rf) against the mean excess returns predicted by four models. Each option portfolio is labeled in a way that the first two digits refer to maturity, C or P stand for call or put, and the last two digits denote moneyness. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \alpha\mathbf{1} + \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of the average excess returns, α is the excess zero-beta rate, and ξ is the vector of pricing errors. The predicted mean excess returns are $\alpha\mathbf{1} + \beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XII for the factor mimicking portfolios.). The sample is monthly from 4/1986-1/2012, but returns are expressed in percentage terms per quarter.

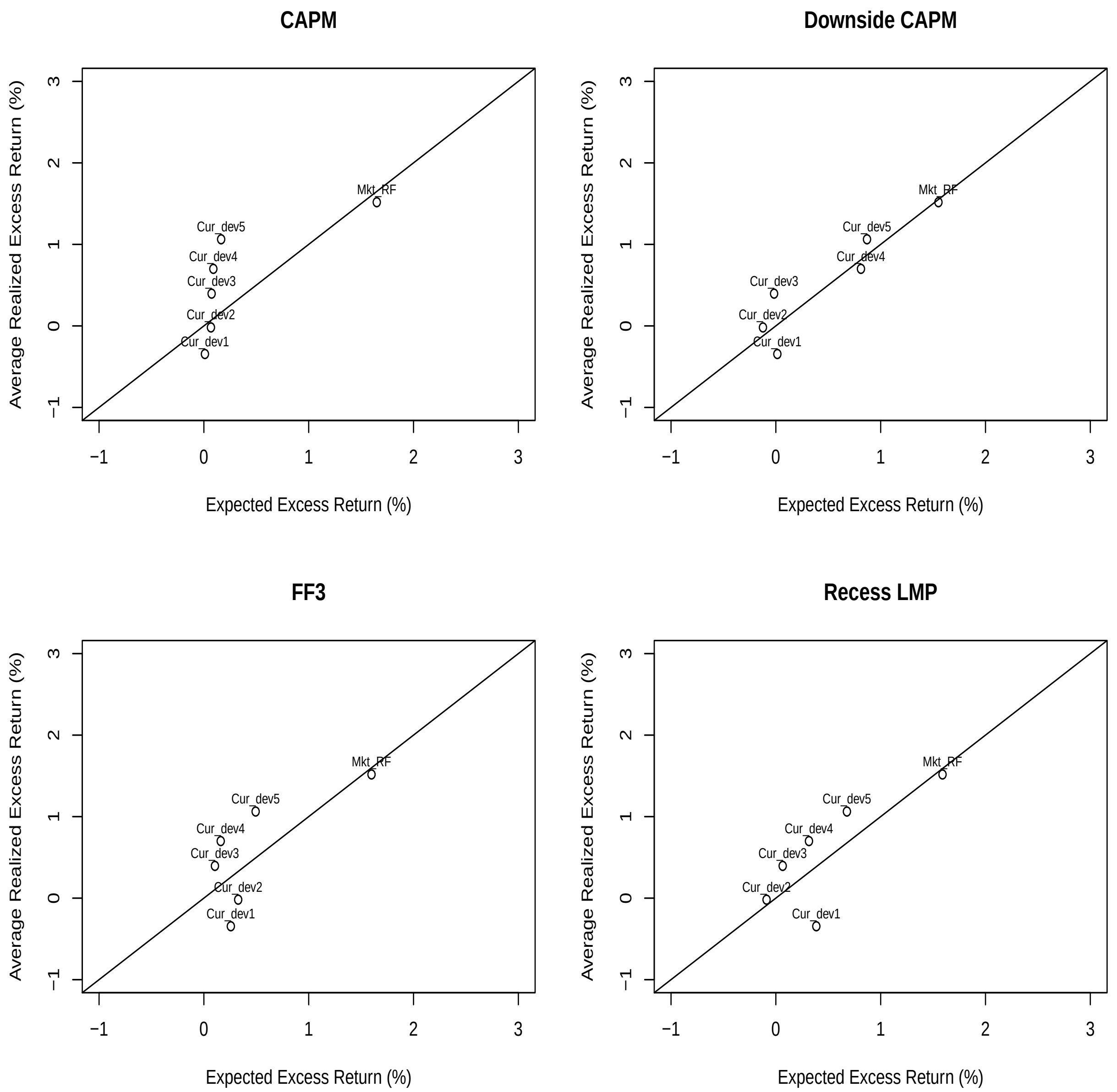

Figure 8: **Pricing Monthly Excess Returns on the Developed Countries' Currency Portfolios, 1/1974-3/2010, 435 Months**

Figure 8 plots the average realized excess returns on the 5 portfolios of currencies of developed countries sorted on nominal interest rates (labeled Cur_dev1-Cur_dev5) and the CRSP value-weighted index (labeled Mkt_rf) against the mean excess returns predicted by four models. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of the average excess returns, and ξ is the vector of pricing errors. The predicted mean excess returns are $\beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XII for the factor mimicking portfolios.). The sample is monthly from 1/1974-3/2010 but returns are expressed in percentage terms per quarter.

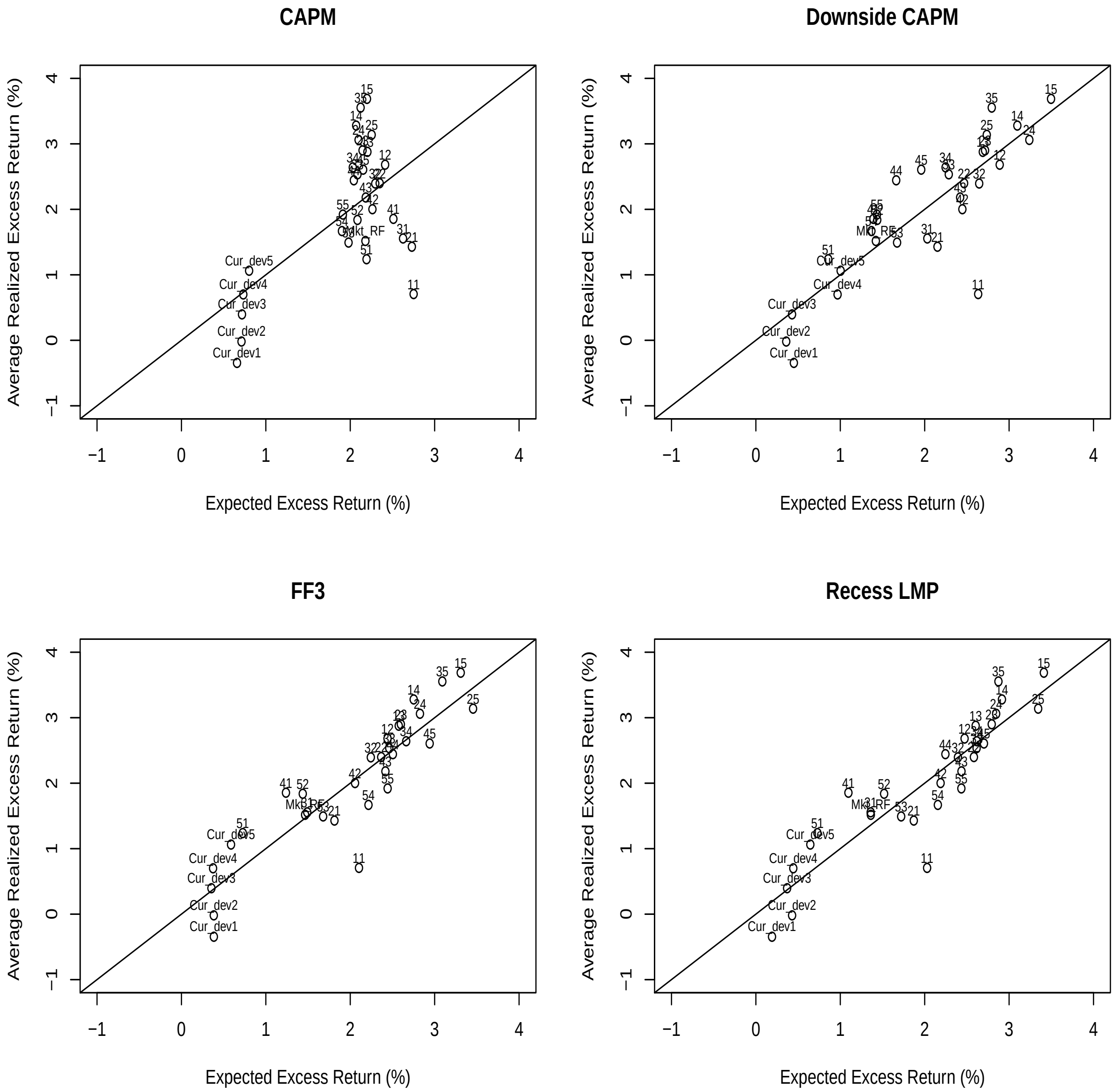

Figure 9: **Pricing Monthly Excess Returns on the Developed Countries' Currency and the Fama-French 25 Size- and Book-to-market-sorted Portfolios, 1974-2010**

Figure 9 plots average realized excess returns on the 5 portfolios of currencies of developed countries sorted on nominal interest rates (labeled Cur_dev1-Cur_dev5), the 25 Fama-French size- and book-to-market-sorted portfolios (labeled 11-55), and the CRSP value-weighted index (labeled Mkt_rf) against the average excess returns predicted by four models. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \alpha\mathbf{1} + \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of the average excess returns, α is the excess zero-beta rate, and ξ is the vector of pricing errors. The predicted mean excess returns are $\alpha\mathbf{1} + \beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XII for the factor mimicking portfolios.). The sample is monthly from 1/1974-3/2010, but returns are expressed in percentage terms per quarter.

Appendices

A Variable Definitions

- Industrial production: Seasonally adjusted industrial production index (INDPRO). Data source: Federal Reserve Economic Data (FRED).

- Real GDP: Quarterly seasonally adjusted final revised real GDP (GDPC1) in billions of chained 2009 dollars. Data source: FRED.

- Real per capita consumption: Aggregate consumption is measured by the sum of personal consumption expenditures on nondurable goods and services. Quarterly seasonally adjusted nominal personal consumption expenditures on nondurable goods and services are taken from the National Income and Product Accounts (NIPA) Table 2.3.5. These nominal consumption expenditures are deflated by their associated price indices from the NIPA Table 2.3.4 and are divided by the total population from the NIPA Table 2.1 to derive real per capita consumption. Data source: NIPA.

- Real per capita labor income: Following Jagannathan and Wang (1996), the nominal aggregate labor income is measured as the difference between the total personal income and the income from dividend. The real per capita labor income is the nominal aggregate labor income divided by total population and deflated by the Consumer Price Index (CPI) from Bureau of Labor Statistics (BLS). Data source: NIPA, BLS.

- Default spread: Spread between Moody's BAA and AAA corporate bond yields. Data source: FRED.

- Term spread: Spread between 10- and 1-year constant maturity Treasury yields. Data source: FRED.

- CRSP dividend-price ratio: CRSP monthly nominal dividends are derived from the difference between cum-dividend and ex-dividend monthly returns on the CRSP value-weighted index, multiplied by the previous month's ex-dividend CRSP index (Fama and French, 1988). The nominal dividends are deflated into real dividends by the CPI. The log dividend-price ratio is the logarithm of the annualized real dividends, formed as the past twelve month trailing sum of real dividends, divided by the current ex-dividend real CRSP index. The ex-dividend real CRSP index is the ex-dividend CRSP index deflated by the CPI. Data source: CRSP, BLS.

- Short-term nominal interest rate: Three-month T-Bill rate (secondary market rate). Data source: FRED.