The Cross-Section and Time Series of Stock and Bond Returns

Ralph S.J. Koijen* LBS & CEPR

Hanno Lustig† UCLA & NBER

Stijn Van Nieuwerburgh‡ NYU, NBER, & CEPR

April 24, 2015

Abstract

We show that bond factors which predict future U.S. economic activity at business cycle horizons are priced in the cross-section of U.S. stock returns. High book-to-markets stocks have larger exposures to these bond factors than low book-to-market stocks, because their cash flows are more sensitive to the business cycle. Because of this new nexus between stock and bond markets, a parsimonious three-factor dynamic no-arbitrage model can be used to jointly price the book-to-market stock and maturity-sorted bond portfolios and reproduce the time-series variation in expected bond returns. The business cycle itself is a priced state variable in stock and bond markets. JEL: G12

*London School of Business, London, NW1 4SA; rkoijen@london.edu; `http://www.koijen.net`. Koijen is also associated with Netspar (Tilburg University).

†Department of Finance, Anderson School of Management, University of California at Los Angeles, Box 951477, Los Angeles, CA 90095; hlustig@anderson.ucla.edu; `http://www.anderson.ucla.edu/faculty/finance/faculty/lustig`.

‡Department of Finance, Stern School of Business, New York University, 44 W. 4th Street, New York, NY 10012; svnieuwe@stern.nyu.edu; `http://www.stern.nyu.edu/ svnieuwe`.

Value investors buy stocks that have low prices relative to measures of fundamentals such as dividends or book assets, and sell stocks that have high prices relative to fundamentals. These strategies earn high returns that appear anomalous relative to standard models such as the CAPM (e.g., Basu, 1977; Fama and French, 1992). The profession has hotly debated whether these superior returns reflect a behavioral bias or a compensation for systematic risk. Under the behavioral hypothesis, extrapolative investors push up the price of growth ("glamour") stocks that performed well in the recent past, allowing contrarian investors to profit from their over-optimism by investing in out-of-favor value stocks and/or shorting the growth stocks (De Bondt and Thaler, 1985). Leading risk-based explanations of the value premium rely on differences in the riskiness of assets in place relative to growth options (Zhang (2005)) or differences in the duration of cash flows of value and growth stocks (Lettau and Wachter (2007)).

Early attempts to connect the cash flows of value and growth firms to macro-economic sources of risk were unsuccessful (Lakonishok, Schleifer, and Vishny, 1994). Our paper provides new evidence that links the excess returns on high minus low book-to-market stock portfolios to cash flow and output risk at business cycle frequencies. We study a much longer sample with more adverse macroeconomic events than previously examined (1926-2011 compared to 1968-1989 in (Lakonishok, Schleifer, and Vishny, 1994), or 15 recessions compared to 4). We develop and apply a new methodology to study macroeconomic events as well.

The connection between the value spread and the macro-economy is easiest to detect in the bond market. We study several linear combinations of bond yields that forecast future economic activity: the Cochrane-Piazzesi factor (CP, Cochrane and Piazzesi (2005)), the slope of the term structure, and the best linear predictor of economic activity at the one-year horizon. We show that innovations in these bond market factors strongly co-move with the returns on value-minus-growth. Since the bond market variables isolate a component of expected growth that is not persistent, our findings assign a central role to the business cycle as a priced state variable.

Our paper makes three contributions. The first contribution is to document that value portfolio returns have a higher covariance with innovations in the bond factors that predict future economic activity at business cycle horizons than growth portfolio returns, consistent with a value premium provided that bond factor innovations carry a positive risk price. Since these innovations represent good news about future output growth and thus lower the marginal utility of wealth for an average forward-looking investor, it is natural that investors assign them a positive risk price.

The second contribution is to attribute these different bond exposures to differences in the underlying cash flow dynamics. We find that value stocks experience negative cash-flow shocks in economic downturns. There are large differences in the behavior of cash-flow growth on value and growth over the macro-economic cycle. For example, over the course of the average NBER recession, dividends on value stocks fall 21% while dividends on growth stocks increase by 3%. The 24% average gap hides interesting differences across recessions. During the Great Recession of 2007-2009, the fall in value-minus-growth dividends was -36%. During the Great Depression (1929-1933) the relative change was -96%. The drop measured during recession months understates the drop during the broader bust period because the NBER recession dates are not perfectly aligned with the dividend cycle; dividends are slow to adjust. For the ten episodes in our sample that witness a protracted fall in real dividends on the market portfolio (27% decline on average), we find that real dividends on the highest book-to-market portfolio fall by 54% more than those on the lowest book-to-market portfolio.

We also show that periods in which the bond factors are low are also periods of significantly lower future dividend growth rates on the market portfolio and on the value-minus-growth portfolio. On average across low-CP events, dividends on value stocks fall 55% more than those on growth stocks relative to their unconditional mean. Value-growth dividend growth turns negative 5-15 quarters after the low-CP events, compared to a 3-4 quarter lag between the same low-CP events and the level of macro-economic activity.

One useful way to highlight the macro-economic risk in value strategies is to select periods during which value stocks and the value-minus-growth strategy experience exceptionally low returns, which we label “low-value events.” Such low-value events are not only associated with low contemporaneous CP realizations, but also with low future economic activity and lower future dividend growth on value-minus-growth, consistent with a risk-based explanation. This event-based approach allows us to detect the link between prices, cash-flows, and macroeconomic aggregates in high marginal utility states of the world that matter most for pricing. The approach could prove fruitful for investigating other return anomalies and their link to the macro-economy.

Our third contribution is to build on this evidence linking the value spread to the bond factors to develop a parsimonious three-factor model that prices the cross-section of stock and bond returns.

Our first pricing factor consists of innovations to the CP factor (results are similar for the other bond factors that predict future economic activity): differential exposure of the five book-to-market portfolios accounts for the average value spread in the data. Second, differential exposure to shocks to the level of the term structure accounts for the difference in excess returns on five maturity-sorted government bond portfolios, consistent with Cochrane and Piazzesi (2008). Third, exposure to the market return accounts for the aggregate equity premium. This three-factor model reduces mean absolute pricing errors on our test assets from 4.89% per year in a risk-neutral benchmark economy to 0.45% per year. By having the price of level risk depend on the lagged bond factor, the model also captures the predictability of bond returns by the CP factor. All of the estimated risk prices have the expected sign, and are collectively significantly different from zero. We cannot reject the null hypothesis that the model's pricing errors are jointly zero.

We explore the robustness of the results for different sub-samples and for different sets of test assets. We construct a factor-mimicking portfolio of the CP shocks. We show that this traded risk factor explains test asset returns as well as the model with CP shocks and with a similar market price of CP risk. We emphasize that the model prices well a set of corporate bond portfolios sorted by credit rating, jointly with equity and government bond portfolios. Finally, we present individual stock-level evidence that exposure to the CP shocks is priced and results in a higher risk premium on stocks. If we estimate our model using portfolios sorted by their CP betas, we find a similar risk price as with the other cross-sections.

What results is a coherent picture of value-minus-growth returns, the bond yield factor, macroeconomic activity, and dividend growth on value-minus-growth that is potentially consistent with a risk-based resolution of the value premium puzzle. A parsimonious stochastic discount factor model provides unified pricing in stock and bond markets.

The rest of the paper is organized as follows. Section 1 contains the related literature discussion. Section 2 reports the main results documenting the link between CP and the macro-economy, while Section 3 contains the main asset pricing results. Section 4 discusses robustness to bond yield factors other than CP, such as the slope of the yield curve, studies the importance of the business-cycle component, and studies alternative test assets including portfolios formed based on firm-level CP betas. Section 5 concludes.

1 Related Literature

Researchers working in a small but growing literature model stock and bond returns jointly, most often in affine settings like ours. They have mostly examined the relation between the aggregate stock and bond markets,[1] with the exception of Lettau and Wachter (2009) and Gabaix (2012), who also study the cross-section of stock returns. The former is a model with common shocks to the risk premium in stock and bond markets, while the latter is a time-varying rare disasters model. In addition, work in production-based asset pricing has linked the investment behavior of value and growth firms during recessions to the value premium (Zhang, 2005).

The business cycle itself plays a secondary role in modern dynamic asset pricing theory.[2] We uncover new evidence that the business cycle in output and consumption growth is itself a priced state variable in stock markets. Value stock returns are more sensitive than growth stock returns to innovations in bond market factors such as CP. Therefore, they are more exposed to cyclical news about the economy's future cash flow growth, because their subsequent cash flow growth is more sensitive to output growth. Value stocks earn a premium as a result. Relative to existing dynamic asset pricing models, our work uncovers the cyclical component in expected output growth as a new priced state variable, distinct from the low frequency state variables in long-run risk of Bansal and Yaron (2004) and external habit models of Campbell and Cochrane (1999). These models are designed to match the lower frequency variation in the market dividend yield.[3] Whether the market price assigned to transitory business cycle risk in existing dynamic asset pricing models is large enough to match equity market, value, and bond risk premia with reasonable parameter choices is an open question.

Our paper advances the empirical ICAPM literature, starting with the seminal work of Chen, Roll,

[1]Examples are Bakshi and Chen (2005) and Bekaert, Engstrom, and Xing (2009) in a Gaussian setting and Campbell, Sunderam, and Viceira (2012) in a linear-quadratic model. Lustig, Van Nieuwerburgh, and Verdelhan (2013) price both nominal bond yields and the aggregate stock market return in a no-arbitrage model in order to measure the wealth-consumption ratio in the data; they do not study the cross-section of bond nor stock returns.

[2]A related literature studies the temporal composition of risk in asset prices, (e.g., Cochrane and Hansen, 1992; Kazemi, 1992; Bansal and Lehman, 1997; Hansen, Heaton, and Li, 2008).

[3]These models are successful in accounting for many of the features of both stocks and bonds. For the external habit model, the implications for bonds were studied by Wachter (2006) and the implications for the cross-section of stocks were studied by Menzly, Santos, and Veronesi (2004) and Santos and Veronesi (2010). Likewise, the implications of the long-run risk model for the term structure of interest rates were studied by Piazzesi and Schneider (2006), Kung (2014), and Bansal and Shaliastovich (2010), while Hansen, Heaton, and Li (2008) study the implications for the cross-section of equity portfolios.

and Ross (1986). These authors use term structure factors either as a predictor of the aggregate return on the stock market or as a conditioning variable in an estimation of a conditional beta model of the cross-section of stock returns. Ferson and Harvey (1991) study stock and bond returns' sensitivity to aggregate state variables, one of which is the slope of the yield curve. They conclude that time variation in equity risk premia is important for understanding the cross-sectional variation in size and industry equity portfolios, and that time variation in interest rate risk premia are important for understanding the cross-sectional variation in bond return portfolios. Brennan, Wang, and Xia (2004) write down an ICAPM model where the real rate, expected inflation, and the Sharpe ratio move around the investment opportunity set and show that this model prices the cross-section of stocks. Similarly, Petkova (2006) studies the connection between the Fama-French factors and innovations in state variables such as the default spread, the dividend-price ratio, the yield spread, and the short rate. Using a VAR model, Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2010) argue that common variation in book-to-market portfolio returns can be attributed to news about future cash flow growth on the market. In this approach, the cash flow innovations are highly persistent. In contrast to this literature, our focus is on the joint pricing of stock and bond returns, business cycle shocks, and the link with dividend growth on stock portfolios. Baker and Wurgler (2012) show that government bonds co-move most strongly with "bond-like stocks," which are stocks of large, mature, low-volatility, profitable, dividend-paying firms that are neither high growth nor distressed. They propose a common sentiment indicator that drives stock and bond returns.

2 Measuring Business Cycle Risk in Value Stocks

In this section, we provide new evidence that value stocks are risky. We start by documenting that value stocks suffer from bad cash-flow shocks at times when a representative investor faces high marginal utility growth. Because dividends adjust to bad shocks with a lag, it is natural to look for early indicators of poor future economic performance. Researchers have traditionally looked at bond markets for expectations about future economic activity. We follow in that tradition and document the predictive ability of several linear combinations of bond yields. These bond market variables are strong predictors of both future aggregate economic activity, future aggregate dividend growth, and future dividend growth on value-minus-growth stock portfolios. To bolster the macro-economic risk explanation, in the last part of this section, we examine periods where realizations on both the value and the value-minus-growth portfolios are exceptionally low, and finds that these are periods characterized by bad news about future aggregate economic activity. The main text focuses on the CP factor as the bond factor, while Section 4 shows the robustness of all results to alternative factors such as the slope of the yield curve and the linear combination of bond yields that best forecasts economic growth.

2.1 Cash-Flow Risk in Value-Growth and the Business Cycle

We use monthly data from the Center for Research on Securities Prices (CRSP) on dividends and inflation from July 1926 until December 2012 (1,038 observations). Inflation is measured as the change in the Consumer Price Index from the Bureau of Labor Statistics. We use the return on the value-weighted NYSE-AMEX-NASDAQ index from CRSP as the market return. Dividends on book-to-market-sorted quintile portfolios are calculated from cum-dividend and ex-dividend returns available from Kenneth French's data library. To eliminate seasonality in dividends, we construct annualized dividends by adding the current month's dividends to the dividends of the past 11 months.[4] We form log real dividends by subtracting the log of the consumer price index from the log of nominal dividends. Our focus is on cash dividends.[5] It is important to note that all quintile portfolios, including the growth portfolio 1, distribute substantial amounts of dividends. The average annual dividend yield varies only modestly across book-to-market quintile portfolios: 2.5% (portfolio 1), 3.5% (2), 3.9% (3), 4.0% (4), and 3.0% (5). The market portfolio has an average dividend yield of 3.4%.

In the left panel of Figure 1, we plot log real dividends on book-to-market quintile portfolios 1 (G for growth), 5 (V for value), and the market portfolio (M) against the NBER recession dates defined by the NBER's Business Cycle Dating committee. For consistency with the asset pricing results that are to follow, we focus on the post-1952.7 sample. The figure shows strong evidence that

[4]Investing dividends at the risk-free rate yields similar results. Binsbergen and Koijen (2010) show that reinvesting monthly dividends at the market return severely contaminates the properties of dividend growth.

[5]Cash dividends are the right measure in the context of a present-value model that follows a certain portfolio strategy, such as value or growth (Hansen, Heaton, and Li, 2008). An alternative is to include share repurchases to cash dividends, but this would correspond to a different dynamic strategy (Larrain and Yogo, 2007). However, in the most recent recession, which is the largest downturn in cash dividends during the period in which repurchases became more popular, share repurchases also declined substantially. This suggests that during the episodes that we are most interested in, cash dividends and share repurchases comove positively and are exposed to the same aggregate risks.

the dividends on value stocks fall substantially more in recessions than those of growth stocks. Value stocks' cash flows show strong cyclical fluctuations whereas dividends on growth stocks are, at best, a-cyclical. The picture for the pre-1952 period, reported in Appendix A, is consistent with this behavior. The two starkest examples of the differential cash-flow behavior of value and growth are the Great Depression (September 1929 - March 1933) and the Great Recession (December 2007 - June 2009), but the same pattern holds during most post-war recessions (e.g., 1973, 1982, 1991, 2001). During the Great Depression, the log change in real dividends from the peak to the through of the cycle is -356% for value, -62% for the market, and -38% for Growth. In the Great Recession, dividends fall 35% for value, 14% for the market, while growth dividends actually rise 10%.

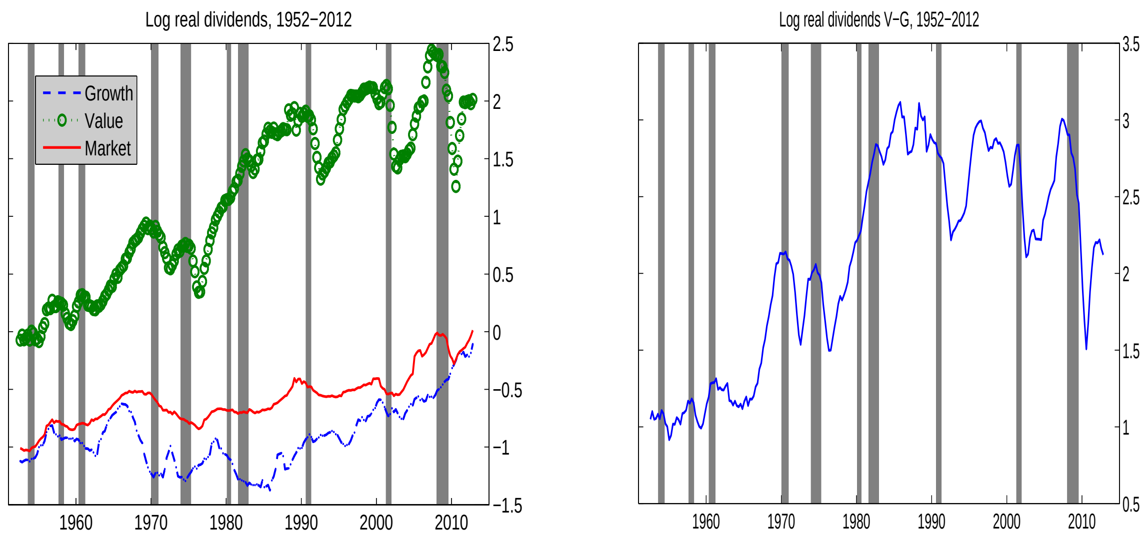

Figure 1: Dividends on value, growth, and market portfolios.

The left panel shows the log real dividend on book-to-market quintile portfolios 1 (growth, dashed line with squares) and 5 (value, dotted line with circles) and on the CRSP value-weighted market portfolio. The right panel shows the log real dividend on book-to-market quintile portfolios 5 (value) minus the log real dividend on the boot-to-market portfolio 1 (growth), plotted against the right axis. The grey bars indicate official NBER recession dates. Dividends are constructed from the difference between cum- and ex-dividend returns on these portfolios, multiplied by the previous month's ex-dividend price. The ex-dividend price is normalized to 1 for each portfolio in 1926.06. Monthly dividends are annualized by summing dividends received during the year. We take logs and subtract the log of the CPI price level (normalized to 100 in 1983-84) to obtain log real dividends. The data are monthly from July 1952 until December 2012 and are sampled every three months in the figure.

Strictly adhering to the NBER recession dates understates the change in dividends from the highest to their lowest point over the cycle. For example, annual dividends on value-minus-growth fall by 45% during the Great Recession, but they fall another 11% between April and December of 2007 and 106% from June 2009 until June 2010. Thus, the total decline measured from May 2007 until June 2010 is 162%, eclipsing the 45% decline over the official NBER cycle. The right panel of Figure 1 shows the log difference between value and growth portfolios (right axis) as well as NBER recessions (bars). The figure illustrates not only large declines in dividends on value-minus-growth around recessions, as well a lag in the declines when compared to the NBER peak. This may reflect the downward stickiness in dividend adjustments that is well understood in the literature on firms' dividend payment behavior.[6]

To examine these broader boom-bust cycles in dividends more systematically, we define busts as periods where real dividends from the market portfolio drop by 5% or more over a protracted period (6 months or more). There are ten such periods in the 1926 to 2012 sample. They last an average of 31 months and real dividends from the market portfolio fall by 27% on average. Real dividends from the growth portfolio fall by 15% on average, while those from the value portfolio fall by 68%, a difference of 54%. For comparison, during the average NBER recession, dividends from value-minus-growth fall by 24%. The periods with large sustained decreases in real dividends on the market are associated with much larger declines in the dividends from value than from growth, which are fifty percent larger than the decline in the market dividend growth itself.

2.2 Bond Factors and the Business Cycle

Having shown that dividends on value-minus-growth fall during and after recessions, this section shows that bond yield factors predict the incidence of recessions. Here, we show that the CP factor forecasts aggregate economic activity, aggregate dividend growth, and dividend growth on value-minus-growth stock portfolios. We follow Cochrane and Piazzesi (2005) in constructing the CP factor as a linear combination of 2- through 5-year government bond yields that bests forecasts future excess bond returns.[7] Appendix A shows that these results extend to two alternative linear combinations: the slope of the yield curve and the linear combination of bond yields that best forecasts future economic activity. Our findings contribute to the recent literature that links bond market variables to macroeconomic

[6] For example, Yoon and Starks (1995) present evidence that firms cut their dividends much less frequently than they increase them, but when they cut them, they cut them at a rate that is five times larger than when they increase them. See also Chen (2009) for aggregate evidence on dividend smoothing.

[7] We use monthly Fama-Bliss zero-coupon yield data, available from June 1952 until December 2012, on nominal government bonds with maturities of one- through five-years to construct one- through five-year forward rates. We then regress the equally-weighted average of the one-year excess return on bonds of maturities of two, three, four, and five years on a constant, the one-year yield, and the two- through five-year forward rates. The yields are one-year lagged relative to the return on the left-hand side. The CP factor is the fitted value of this predictive regression. The R^2 of this regression in our sample of monthly data is 18.1%, roughly twice the 10.3% R^2 of the five-year minus one-year yield spread, another well-known bond return predictor.

activity.[8]

We consider the following predictive regression in which we forecast future economic activity, measured by the Chicago Fed National Activity Index ($CFNAI$),[9] using the current CP factor:

$$CFNAI_{t+k} = c_k + \beta_k CP_t + \varepsilon_{t+k}, \tag{1}$$

where k is the forecast horizon expressed in months. The regressions are estimated by OLS and we calculate Newey-West standard errors with $k-1$ lags. The sample runs from March 1967 until December 2012 (550 months), dictated by data availability. The left panels in Figure 2 show the coefficient β_k in the top panel, its t-statistic in the middle panel, and the regression R-squared in the bottom panel. The forecast horizon k is displayed on the horizontal axis and runs from 1 to 36 months. CP is strongly and significantly positively associated with future economic activity. All three statistics display a hump-shaped pattern, gradually increasing until approximately 12-24 months and then gradually declining afterwards. The maximum slope is 24.9, with a t-statistic of 4.2 and an R^2 of 14.7%. This maximum predictability is for $CFNAI$ 21 months later. From Figure 2 we infer that a high CP factor precedes higher economic activity about 12 to 24 months later. At the 24-month horizon, CP is close to the best predictor in the class of linear combinations of 1- through 5-year bond yields. The predictability is statistically significant for horizons from 1 month to 31 months. Appendix A shows similar results when forecasting GDP growth rather than $CFNAI$.

Having shown earlier that both aggregate dividend growth and dividend growth on value-minus-growth stocks declines around recessions, we now ask whether the bond yield factor (CP) predicts aggregate dividend growth and dividend growth on value-minus-growth stocks. We employ linear

[8] Brooks (2011) shows that the CP factor has a 35% contemporaneous correlation with news about unemployment, measured as deviations of realized unemployment from the consensus forecast. Gilchrist and Zakrajsek (2012) shows that a credit spread, and in particular a component related to the bond risk premium, forecasts economic activity. A related literature examines the predictability of macro-economic factors for future bond returns. Cooper and Priestley (2008) show that trend deviations in industrial production forecast future bond returns; Joslin, Priebsch, and Singleton (2010) incorporate this finding in an affine term structure model. Ludvigson and Ng (2009) shows that a principal component extracted from many macroeconomic series also forecasts future bond returns. While macro-economic series do not fully incorporate the variation in bond risk premia, there clearly is an economically meaningful link between them.

[9] The $CFNAI$ is a weighted average of 85 existing monthly indicators of national economic activity. $CFNAI$ peaks at the peak of the business cycle and bottoms out at the through. Since economic activity tends toward trend growth over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend. $CFNAI$ is normalized to have mean zero and standard deviation one.

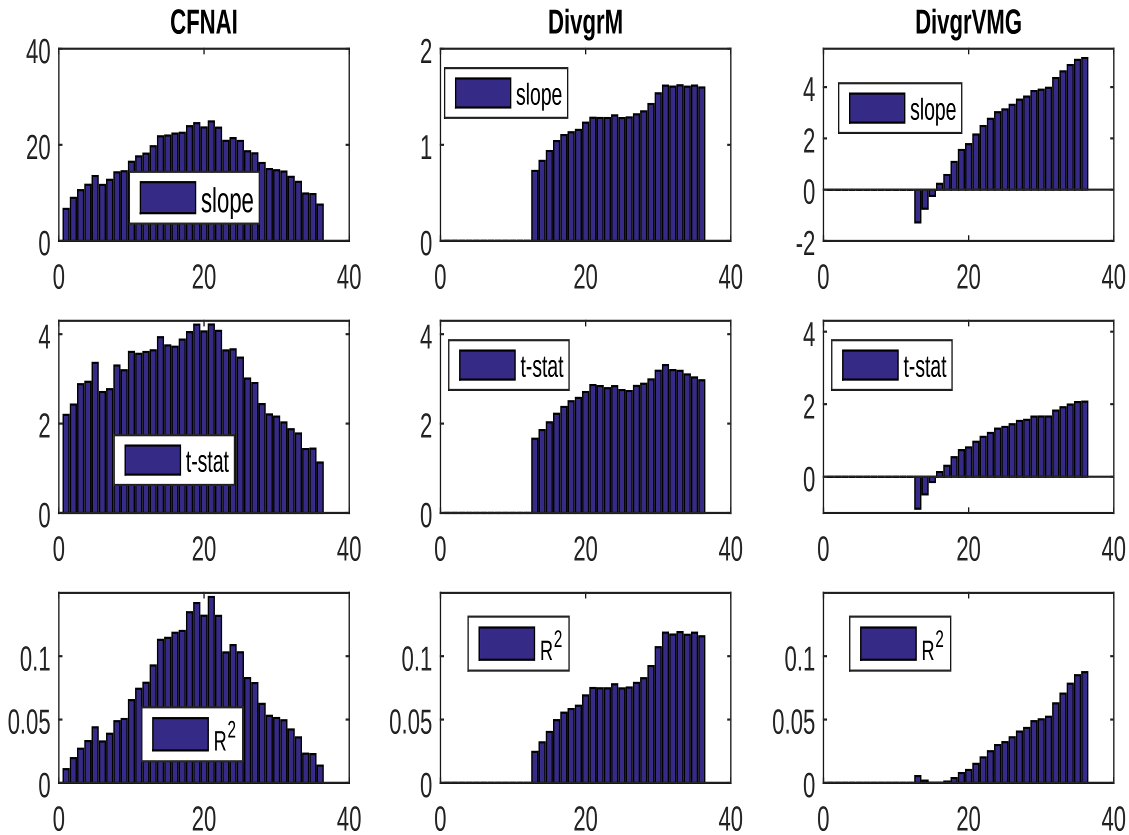

Figure 2: Economic activity predicted by bond factors.

The top panel displays the predictive coefficient β_k in (1), the middle panel the t-statistic, and the bottom panel the corresponding R^2. We consider $k = 1, \dots, 36$ months of lags, displayed on the horizontal axis in each panel, and the t-statistics are computed using Newey-West standard errors with $k-1$ lags. In all three columns, the predictor is the CP factor. In the left column, $CFNAI_{t+k}$ is the dependent variable. In the middle column, the aggregate dividend growth rate Δd_{t+k} is the dependent variable. In the last column, the dividend growth rate on value minus growth $\Delta d^V_{t+k} - \Delta d^G_{t+k}$ is the dependent variable. The sample is March 1967 until December 2012.

regressions like equation (1). Since dividend growth is constructed using 12 months of data, we only consider horizons $k \geq 12$. The predictive coefficients, t-statistics, and R-squared values for the aggregate dividend growth on the market (value minus growth) are summarized in the middle (right) column of Figure 2. CP strongly predicts aggregate dividend growth, especially 2-3 years out. The right column shows that our bond market variable also linearly predict dividend growth on value-minus-growth. The predictability of CP is concentrated at longer horizons of 33-36 months ahead. Table A.I in the Appendix contains the point estimates. This regression evidence implies that bond markets contains useful information about future cash flow growth in the aggregate and about differential cash-flow prospects for value and growth firms.

2.3 A Macro-Event Study of Value

In this section, we further explore the connection between value and growth returns, CP, and the macro-economy.

2.3.1 Low-CP Events

While the bond yield variables clearly lead the cycle, their exact timing vis-a-vis the official NBER recession dating may b e fragile because the lead-lag pattern may fluctuate from one recession to the next (see Figure A.2 in the Appendix). Thus, it may be informative to isolate periods in which CP is low and then to ask how the level of economic activity behaves around such events.

In each quarter since 1952.Q3 we compute quarterly CP as the CP factor value in the last month of that quarter, and we select the 25% of quarters with the lowest quarterly CP readings. Figure 3 shows how several series of interest behave six quarters before (labeled with a minus sign) until ten quarters after (labeled with a plus sign) the low-CP event, averaged across such events. The quarter labeled '0' in Figure 3 is the event quarter with the lowest CP reading. The top right panel shows the dynamics of CP itself, which naturally falls from a positive value in the preceding quarters to a highly negative value in the event quarter, after which it recovers.

The bottom right panel shows the economic activity index $CFNAI$ over this CP cycle. There is a clear pattern in economic activity in the quarters surrounding the low-CP event. When CP is at its lowest point, economic activity is about average ($CFNAI$ is close to zero). $CFNAI$ then turns negative for the next ten quarters, bottoming out five to six quarters after the CP event. This lead-lag pattern is consistent with the predictability evidence shown above. The change in $CFNAI$ from four quarters before until four quarters after is economically large, representing 1.2 standard deviations of $CFNAI$. The Appendix shows similarly strong dynamics in real GDP growth around low-CP events.

The bottom left panel of Figure 3 shows annual dividend growth on value-minus-growth (fifth-minus-first book-to-market portfolio) over the CP cycle. The dividend growth differential is demeaned over the full sample, so as to take out the trend in the dividend growth rate differential. Dividend growth on value-minus-growth is high when CP is at its nadir and starts falling immediately afterwards.

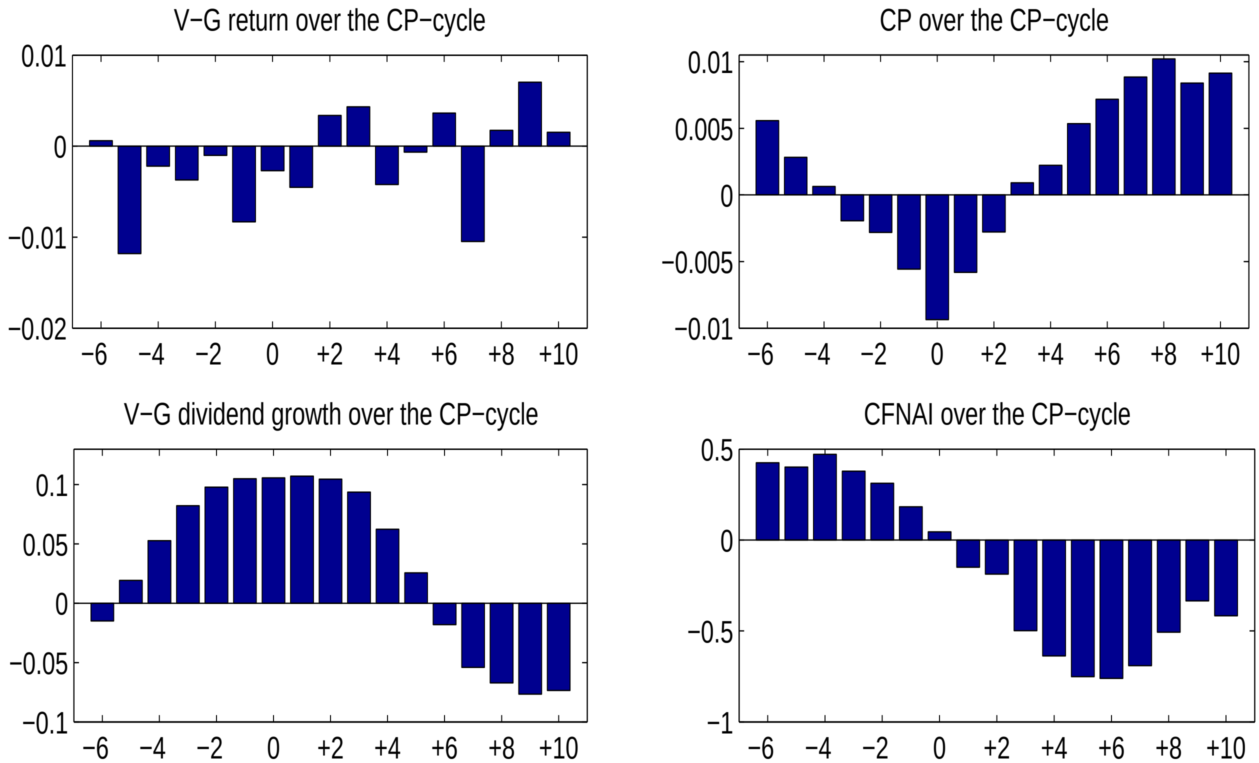

Figure 3: Low CP events

The figure shows four quarterly series in event time. The event is defined as a quarter in which the quarterly CP factor in its respective lowest 25% of observations. This selection leads to 60 events out of 242 quarters. The sample runs from 1953.Q3 until 2012.Q4. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The top left panel plots the realization of the quarterly log return on value-minus-growth. The bottom left panel reports annual log dividend growth on value-minus-growth. The top right panel plots the CP factor. The bottom right panel plots the $CFNAI$ index of economic activity. The latter is available only from 1967.Q2 onwards. Formally, the graph reports $c_k + \beta_k$ from a regression $X_{t+k} = c_k + \beta_k \mathcal{I}_{CP_t < LB} + \epsilon_{t+k}$, for various k, where $\mathcal{I}$ is an indicator variable, LB is the 25th percentile of CP, and X is the dependent variable which differs in each panel. Value-minus-growth returns and value-minus-growth dividend growth have been demeaned over the full sample; $CFNAI$ is also mean zero by construction.

This decline in value-minus-growth dividend growth is persistent and economically large. Over the ten quarters following the CP event, annual dividends on value stocks fall by 20.8% points more than on growth stocks, a 0.9 standard deviation decline. Dividend growth on value-minus-growth (relative to its unconditional mean) stays negative until 15 quarters after the event (not shown). Cumulative value-minus-growth dividend growth between the end of quarters 6 and 15 is -55%. That means that dividends on value stocks are 55% lower than those on growth stocks, relative to trend, on average after low-CP events. Comparing the bottom two panels, we see that dividend growth lags economic activity by several quarters. This lagged reaction arises in part because firms are reluctant to cut dividends, and only do so after a bad shock (like a low-CP event). In other part, the lag arises from the construction of the dividend growth measure. Since dividend growth is computed using the past twelve months of dividends, it is not until the end of quarter +4 that all dividends, used in the measured growth rate, are realized after the time-0 shock. In sum, low CP realizations predict low future dividend growth rates on value-minus-growth, but with a considerable lag. This evidence confirms the formal regression evidence discussed above.

Finally, the top left panel of Figure 3 shows quarterly returns on value-minus-growth. The value spread is demeaned over the full sample. The evidence presented in the introduction suggests a link between *innovations* in CP and returns on value-minus-growth. This panel is consistent with that evidence. Between quarters -2 and -1 and -1 and 0, the CP factor falls sharply while between quarter 0 and +1, CP rises sharply. The top LHS figure shows that realized returns on the value-minus-growth strategy are negative in quarter -1 and but rises in quarter 0 and 1 (at which point they are slightly positive once we add back in the 0.5% quarterly mean). This is consistent with the higher exposure of value stocks to CP innovations than the exposure of growth stocks. The top left panel of Figure 3 provides evidence against the interpretation of the CP shock as a discount rate shock (instead of, or in addition to, a shock to expected cash flows on value-minus-growth). Indeed, for CP shocks and *realized* value-minus-growth returns to be positively contemporaneously correlated, *expected* future returns on value-minus-growth would have to be particularly high upon a negative CP shock. This is belied by the low average value-minus-growth return in the quarters following the low CP event. We return to the relationship between value-minus-growth returns and the CP factor in detail in Section 3.[10] The Appendix shows similar results when we study low yield spread events instead of low CP factor realizations.

2.3.2 Low-value events

Alternatively, we can isolate periods in which value stocks do particularly poorly. Around such periods, we should find evidence of the poor performance of cash-flows and the macroeconomy. To investigate this possibility, we select quarters in which both the realized log real return on value (the fifth book-to-market portfolio) and the realized log return on value-minus-growth (fifth minus first

[10] An adequate description of dividend dynamics contains at least two shocks: one shock that equally affects dividend growth rates on all portfolios, and a second shock (to the CP factor) that affects value dividends relative to growth dividends. The Appendix discusses the evidence against a one-factor model.

book-to-market portfolio) are in their respective lowest 30% of observations. These "low-value events" are periods in which value does poorly in absolute terms as well as in relative terms. The double criterion rules out periods in which value returns are average, but value-minus-growth returns are low because growth returns are high. This intersection leads to 37 events out of 242 quarters (or about 15% of the sample). The top left panel of Figure 4 shows the quarterly log returns on value-minus-growth around the event quarter. The value-minus-growth returns are again demeaned over the full sample. By construction, value-minus-growth returns are low in period 0. They are on average -7%, or -8% below the +1% quarterly mean. The value spread declines modestly in the three quarters leading up to the event and rebounds modestly in the three quarters following the event.

The top right panel of Figure 4 shows that the level of CP falls in the two quarters leading up to the low value-minus-growth return, bottoms out in the quarter of the value-minus-growth return, and increases in the following two quarters. There is a positive *contemporaneous* relationship between value-minus-growth returns and *changes* in the CP factor. This suggests that (innovations in) the CP factor captures the risk associated with low value-minus-growth returns.

The bottom left panel shows that dividend growth on value-minus-growth falls considerably in the aftermath of the low-value return event. Annual dividend growth on value-minus-growth gradually falls by about 7% over the six quarters around the event. Being one-quarter of a standard deviation, it is an economically meaningful drop. Dividend growth on value-minus-growth continues to fall until quarter 12 (not shown). Between the end of quarters 2 and 12, cumulative dividend growth on value-minus-growth is -29.3%, on average across low-value events. This finding dovetails nicely with the fall in dividends on value-minus-growth over the course of recessions, shown above. Indeed, many of the low-value events occur just prior to the official start of NBER recessions.

We see the same decline in macroeconomic activity following a low-value return event. The bottom right panel of Figure 4 shows the level of $CFNAI$. In the event quarter, the level of economic activity is 0.4 standard deviations below average and it stays below average for the ensuing eight quarters. The change in economic activity from two quarters before to two quarters after the event is one-half of a standard deviation of $CFNAI$. The Appendix shows an equally large effect on real GDP growth. The delayed adjustment in dividends vis-a-vis that of macroeconomic activity is consistent with that found in the low-CP event analysis. The evidence in the bottom two panels suggests that firms only

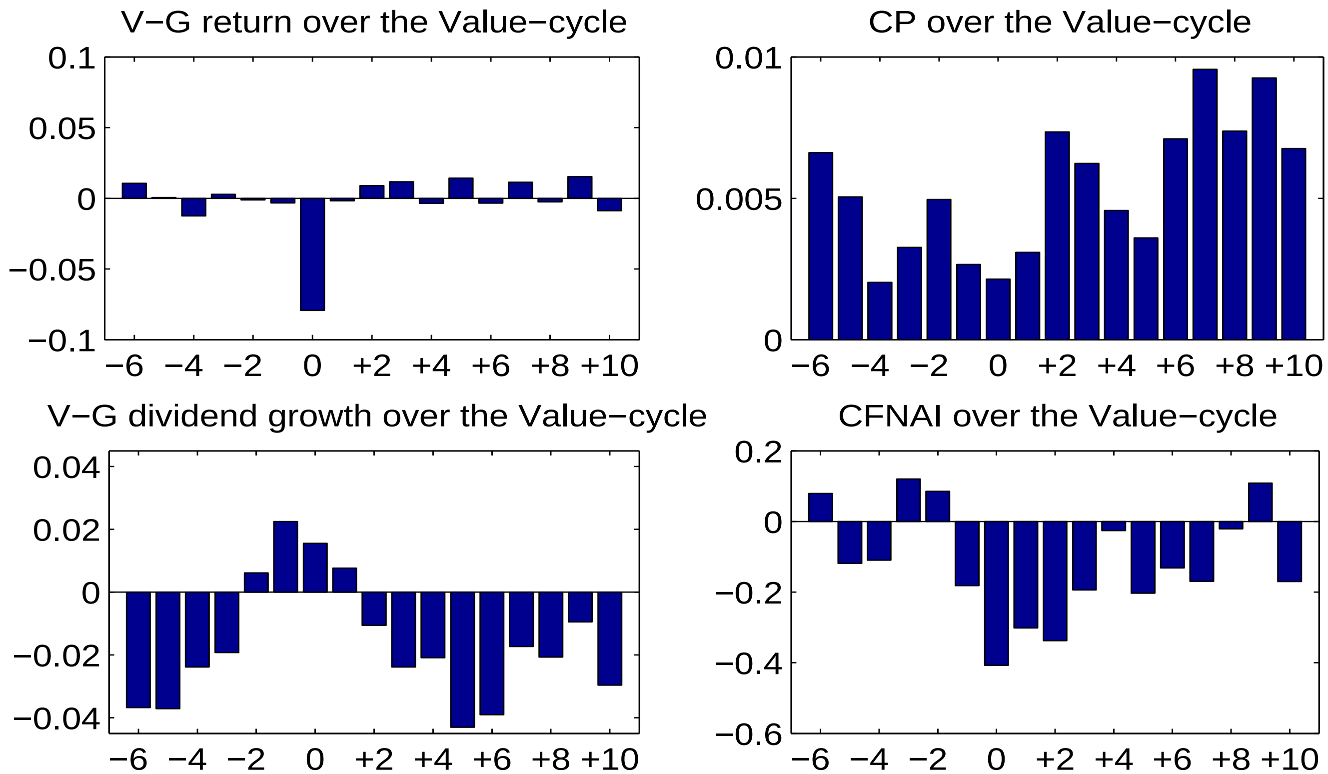

Figure 4: Low-value events

The figure shows four quarterly series in event time. An event is defined as a quarter in which both the realized log real return on the fifth book-to-market portfolio (value) and the realized log return on value-minus-growth (first book-to-market portfolio) are in their respective lowest 30% of observations. This intersection leads to 37 events out of 242 quarters (15%). The sample runs from 1953.Q3 until 2012.Q4. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The top left panel plots the realization of the quarterly log return on value-minus-growth. The bottom left panel reports annual log dividend growth on value-minus-growth. The top right panel plots the CP factor. The bottom right panel plots the $CFNAI$ index of economic activity. The latter is available only from 1967.Q2 onwards. Formally, the graph reports $c_k + \beta_{1k} + \beta_{2k}$ from a regression $X_{t+k} = c_k + \beta_{1k}\mathcal{I}_{excret_V < LB_V} + \beta_{2k}\mathcal{I}_{excret_{V,t} - excret_{G,t} < LB_S} + \epsilon_{t+k}$, for various k, where $\mathcal{I}$ is an indicator variable, LB_V is the 30th percentile of excess returns on the value portfolio, LB_V is the 30th percentile of excess returns on the value-minus-growth portfolio, and X is the dependent variable which differs in each of the four panels. Value-minus growth returns and value-minus-growth dividend growth have been demeaned over the full sample; $CFNAI$ is also mean zero by construction.

cut dividends (and those in the value more than those in the growth portfolio) after a prolonged period of below-average levels of economic activity.

Methodologically, the advantage of the event-time approach is that it focuses on those periods where the investment strategy performs poorly. By looking at windows around these low value return events, the relationships between returns, cash flows, and macroeconomic activity become more transparent and therefore easier to detect. While the low value-minus-growth return events are clearly associated with recessions, the exact timing vis-a-vis the official NBER recession dates varies from recession to recession. This makes it hard to detect clear relationships between value returns and NBER recessions.

3 A Factor Model for Stocks and Bonds

Based on the evidence on the link between the value spread and the CP factor, we provide a unified asset pricing model for the cross-section of book-to-market equity portfolios, the equity market portfolio, and the cross-section of maturity-sorted bond portfolios. In a second pass, we also include corporate bond portfolios, sorted by credit rating. Our model is parsimonious in that only three pricing factors are needed to capture the bulk of the cross-sectional return differences. As a reduced-form stochastic discount factor model, it imposes little structure beyond the absence of arbitrage opportunities between these equity and bond portfolios. Appendix D presents a structural asset pricing model, which starts from cash flow growth rather than returns, and formalizes the intuition for the empirical connection between stock returns and stock cash flows, bonds, and the business cycle.

3.1 Setup

Let P_t be the price of a risky asset, D_{t+1} its (stochastic) cash-flow, and R_{t+1} the cum-dividend return. Then the nominal stochastic discount factor (SDF) implies $E_t[M^{\$}_{t+1}R_{t+1}] = 1$. Lowercase letters denote natural logarithms: $m^{\$}_t = \log\left(M^{\$}_t\right)$. We propose a reduced-form SDF, akin to that in the empirical term structure literature (Duffie and Kan, 1996):

$$-m^{\$}_{t+1} = y^{\$}_t + \frac{1}{2}\Lambda'_t\Sigma\Lambda_t + \Lambda'_t\varepsilon_{t+1}, \tag{2}$$

where $y^{\$}_t$ is the nominal short-term interest rate, ε_{t+1} is a $N \times 1$ vector of shocks to the $N \times 1$ vector of demeaned state variables X_t, and where Λ_t is the $N \times 1$ vector of market prices of risk associated with these shocks at time t. The state vector in (3) follows a first-order vector-autoregression with intercept γ_0, companion matrix Γ, and conditionally normally, i.i.d. distributed innovations, $\varepsilon_t \sim \mathcal{N}\left(0, \Sigma\right)$:

$$X_{t+1} = \Gamma X_t + \varepsilon_{t+1}, \tag{3}$$

$$\Lambda_t = \Lambda_0 + \Lambda_1 X_t. \tag{4}$$

The market prices of risk are affine in the state vector, where Λ_0 is an $N \times 1$ vector of constants and Λ_1 is an $N \times N$ matrix that governs the time variation in the prices of risk.

Log returns on an asset j can be stated as the sum of expected and unexpected returns: $r_{t+1}^{j} = E_t[r_{t+1}^{j}] + \eta_{t+1}^{j}$. Unexpected log returns η_{t+1}^{j} are assumed to be normally distributed and homoscedastic. We denote the covariance matrix between shocks to returns and shocks to the state variables by Σ_{Xj}. We define log excess returns to include a Jensen adjustment:

$$rx_{t+1}^{j} \equiv r_{t+1}^{j} - y_t^{\$}(1) + \frac{1}{2}V[\eta_{t+1}^{j}].$$

The no-arbitrage condition then implies:

$$E_t\left[rx_{t+1}^{j}\right] = Cov_t\left[rx_{t+1}^{j}, -m_{t+1}^{\$}\right] = Cov\left[\eta_{t+1}^{j}, \varepsilon_{t+1}'\right]\Lambda_t \equiv \Sigma_{Xj}\left(\Lambda_0 + \Lambda_1 X_t\right). \tag{5}$$

Unconditional expected excess returns are computed by taking the unconditional expectation of (5) to generate:

$$E\left[rx_{t+1}^{j}\right] = \Sigma_{Xj}\Lambda_0. \tag{6}$$

The main object of interest, Λ_0, is estimated below. Equation (6) suggests an interpretation of our model as a simple factor model, where the factor innovations ε are the priced sources of risk. In Appendix B.1, we estimate how the market prices of risk vary with X_t: the matrix Λ_1 is chosen to exactly match the observed predictability of the stock market and the average bond return by the CP factor.[11]

3.2 Data and Implementation

In our main asset pricing result, we explain the average excess returns on the five value-weighted quintile portfolios sorted on their book-to-market ratio from Fama and French (1992), the value-

[11] Time variation in the market prices of risk drives time variation in expected returns, thereby affecting the unexpected returns η_{t+1}^{j} and the unconditional asset pricing model in equation (6). Cochrane and Piazzesi (2005) provide evidence of predictability of the aggregate market return by the lagged CP factor. Ang and Bekaert (2007) study the predictability of interest rates and the slope of the term structure for stock returns. In practise, the time variation in the market prices of risk plays a minor role in our analysis because there is only modest predictability in future stock and bond returns in the data. But whatever predictability there is, we match it through the choice of Λ_1. In addition, we could include the aggregate dividend-price ratio (DP) as a predictor of the stock market. Given the low R^2 of these predictive regressions, the resulting unexpected returns are similar whether we assume predictability by CP, DP, both, or no predictability at all.

weighted stock market return from CRSP (NYSE, AMEX, and NASDAQ), and five zero-coupon nominal government bond portfolios with maturities of 1, 2, 5, 7, and 10 years from CRSP. The return data are monthly from July 1952 until December 2012 (726 observations). In our second exercise, we add corporate bond returns. We use data from Citibank's Yield Book for four investment-grade portfolios: AAA, AA, A, and BBB. Return data for these portfolios are available monthly from January 1980 until December 2012, which restricts our estimation to this sample (396 observations). Section 4 examines other sets of test assets for robustness. We propose three asset pricing factors in X_t. The first factor is the bond factor CP, which forecasts future macro-economic activity, as discussed in Section 2. The second asset pricing factor measures the level of the term structure of interest rates, LVL. It is constructed as the first principal component of the one- through five-year Fama-Bliss forward rates. The third factor, MKT, is the value-weighted stock market return from CRSP.

We construct the unexpected bond returns in η as the residuals from a regression of each bond portfolio's log excess return on the lagged CP factor. Similarly, we assume that stock returns are also predictable by the lagged CP factor, and construct the unexpected stock returns in η as the residual from a regression of each stock portfolio's log excess return on the lagged CP factor.

We estimate a monthly VAR(1) with the CP, LVL, and MKT factors. Innovations to the state vector ε follow from equation-by-equation OLS estimation of the VAR model in (3). The innovation correlations between our three factors are close to zero. When CP, we find correlations of 0.04 between CP and LVL, 0.04 between CP and MKT, and -0.10 between LVL and MKT.

The first column of Table 1 shows the full sample average excess returns, expressed in percent per year for the 11 test assets. They are the pricing errors resulting from a model where all prices of risk in Λ_0 are zero, that is, from a risk-neutral SDF model (*RN SDF*). Average excess returns on bonds are between 1.0 and 2.1% per year and generally increase in maturity. The aggregate excess stock market return is 6.6%, the excess returns on the book-to-market portfolios range from 6.0% (BM1, growth stocks) to 10.1% (BM5, value stocks), implying a value premium of 4.1% per year.

The first column of Table 2 shows the average excess returns for the shorter 1980-2012 sample. Average excess returns on long-dated government bonds are substantially higher in this sample, for example 3.9% per year for the 10-year bond. The equity risk premium is also slightly higher at 6.9% while the value risk premium is slightly lower at 3.3% per year. The rating-sorted corporate bond portfolios have average excess returns between 3.4% per year for the highest-rated portfolio (AAA) and 4.6% for the lowest-rated portfolio (BBB).

We estimate the three risk price parameters in $\hat{\Lambda}_0$ by minimizing the ~~root mean~~ sum of squared pricing errors on our $J = 11$ test assets. Formally, we define the GMM moments, conditional on the second moment matrix Σ_{Xj}, as:

$$g_T(\Lambda_0) = E_T\left[rx^j_{t+1}\right] - \Sigma_{Xj}\Lambda_0, \tag{7}$$

where $E_T[\cdot]$ denotes the sample average. We estimate Λ_0 as:

$$\widehat{\Lambda}_0 = argmin_{\Lambda_0}\; g_T(\Lambda_0)' g_T(\Lambda_0), \tag{8}$$

which is equivalent to regressing the $J \times 1$ average excess returns on the $J \times 3$ covariances in Σ_{XJ}. We use the same objective function in all models that we estimate. Similar to two-pass regressions, the risk price may deviate from the in-sample mean of the factor if the factor is traded. To impose this additional constraint, one could include the factor as a test asset and use the inverse of the covariance matrix of the pricing errors, instead of the identity matrix as we do, as the weighting matrix in (8). However, as we wish to compare the same cross-section of test assets in all of our tests, which do not include, for instance, the Fama and French factors, we do not impose this constraint in our estimation.

3.3 Estimation Results

The results from our model are in the second column of Table 1 (*CP SDF*). Panel A shows the pricing errors. Our model succeeds in reducing the mean absolute pricing errors (MAPE) on the 11 stock and bond portfolios to a mere 45 basis points (bps) per year. The model largely eliminates the value spread: The spread between the fifth and the first book-to-market quintile portfolios is 105 bps per year. We also match the market equity risk premium and the average bond risk premium. Pricing errors on the stock and bond portfolios are an order of magnitude lower than in the first column and substantially below those in several benchmark models we discuss below.

Panel ~~C~~ B of Table 1 shows the point estimates for $\hat{\Lambda}_0$. We estimate a positive price of CP risk,

Table 1: Unified SDF Model for Stocks and Bonds - Pricing Errors

Panel A of this table reports pricing errors on five book-to-market sorted quintile stock portfolios, the value-weighted market portfolio, and five bond portfolios of maturities 1, 2, 5, 7, and 10 years. They are expressed in percent per year (monthly numbers multiplied by 1200). Each column corresponds to a different stochastic discount factor (SDF) model. The first column contains the risk-neutral SDF and therefore reports the average pricing errors to be explained. The second column presents our CP SDF model with three priced risk factors (CP, LVL, MKT). The third column presents the results for a bond pricing model, where only the level factor is priced (LVL). The fourth column (LVL-only bonds) only uses the bond returns as test assets to estimate the same SDF as in the third column. The SDF model of the fifth column has the market return as the only factor (MKT). The sixth column allows for both the prices of LVL and MKT risk to be non-zero. The seventh column refers to a model with the MKT, SMB, and HML factors of Fama and French (1992). In the final column, we use the same SDF as in (2), but we replace the CP innovations with their factor-mimicking portfolio return, as described in equation (9). The last row of Panel A reports the mean absolute pricing error across all 11 test assets (MAPE). Panel B reports the estimates of the market prices of risk Λ_0. In the seventh column, the pricing factors are the innovations in the excess market return (MKT), in the size factor (SMB), and in the value factor (HML), where innovations are computed as the residuals of a regression of these factors on the lagged dividend-price ratio on the market. Panel C reports asymptotic p-values of chi-squared tests of (i) the null hypothesis that all market prices of risk in Λ_0 are jointly zero ($\Lambda_0 = 0$), and (ii) of the null hypothesis that all pricing errors are jointly zero (Pr. err. = 0). The data are monthly from June 1952 through December 2012.

	(1) RN SDF	(2) CP SDF	(3) LVL	(4) LVL only bonds	(5) MKT	(6) LVL, MKT	(7) MKT, SMB, HML	(8) CP^T SDF
Panel A: Pricing Errors (in % per year)								
10-yr	1.76	0.26	-3.90	-0.43	1.35	-0.49	0.37	-0.50
7-yr	2.08	0.43	-2.95	0.13	1.78	0.15	0.90	0.22
5-yr	1.72	-0.29	-2.54	0.07	1.51	0.13	0.82	0.10
2-yr	1.22	-0.86	-0.89	0.41	1.07	0.39	0.76	0.33
1-yr	0.97	-0.61	-0.11	0.55	0.87	0.52	0.72	0.47
Market	6.58	-0.78	5.31	6.08	-1.33	-1.26	0.07	-0.42
BM1	6.01	-0.36	4.76	5.52	-2.28	-2.18	0.47	0.17
BM2	6.92	-0.03	5.45	6.35	-0.76	-0.77	-0.58	-0.02
BM3	7.80	0.61	6.33	7.23	0.62	0.57	-0.51	0.33
BM4	8.56	-0.06	7.09	7.99	1.53	1.47	-0.74	-0.03
BM5	10.14	0.69	9.12	9.75	2.38	2.52	1.05	-0.01
MAPE	4.89	0.45	4.40	4.05	1.41	0.95	0.63	0.24
Panel B: Prices of Risk Estimates Λ_0								
MKT	0	2.27	0	0	3.50	3.29	5.90	2.21
LVL/SMB	0	-19.27	-32.93	-12.75	0	-10.81	-10.17	-13.00
CP/HML	0	95.84	0	0	0	0	6.58	122.05
Panel C: P-values of chi-squared Tests								
$\Lambda_0 = 0$	–	0.25%	0.00%	–	0.04%	0.02%	0.01%	0.00%
Pr. err. = 0	–	5.79%	0.00%	–	0.00%	0.00%	0.02%	0.02%

while the price of LVL risk is negative and that of MKT risk is positive. The signs on these risk prices are as expected. As explained in Section 2, the positive price of CP risk arises because positive shocks to CP are good news for future economic activity, which implies a negative innovation to the SDF or equivalently low marginal utility of wealth states for the representative investor. A positive shock to the level factor leads to a drop in bond prices and negative bond returns. A negative shock to bond returns increases the SDF and, hence, carries a negative risk price. A positive shock to the market factor increases stock returns and lowers the SDF, and should carry a positive risk price. We also compute asymptotic standard errors on the Λ_0 estimates using GMM with the identity weighting matrix. The standard errors are 34.69 for the CP factor price (point estimate of 95.84), 8.70 for the LVL factor price (-19.27), and 1.24 for the MKT factor price (2.27). Hence, the first two risk prices are statistically different from zero (with t-stats of 2.8 and -2.2 respectively), whereas the last one is only significant at the 10% level (t-stat of 1.8).

The penultimate row of Table 1 tests the null hypothesis that the market price of risk parameters are jointly zero. This null hypothesis is strongly rejected. The asymptotic p-value for the chi-squared-test, computed by GMM using the identity weighting matrix, is 0.25% for the CP SDF model.[12] The last row reports the p-value for the chi-squared test that all pricing errors are jointly zero. Interestingly, the null hypothesis cannot be rejected at the 5% level with a p-value of 5.8%. Test of whether individual pricing errors are zero cannot be rejected for all but one of the test assets, namely the aggregate market portfolio (not reported). These tests lend statistical credibility to our results. In sum, our three-factor pricing model is able to account for the bulk of the cross-sectional variation in stock and bond returns with a single set of market price of risk estimates.

Why is our three factor model able to price this cross-section of assets? Figure 5 decomposes each asset's risk premium into its three components: risk compensation for exposure to the CP factor, the LVL factor, and the MKT factor. The top panel shows risk premia for the five bond portfolios, organized from shortest maturity on the left (1-year) to longest maturity on the right (10-year). The bottom panel shows the decomposition for the book-to-market quintile portfolios, ordered from growth to value from left to right, as well as for the market portfolio (most right bar). Panel B shows that all book-to-market portfolios have about equal exposure to both MKT and LVL shocks. If anything,

[12]The Appendix considers a different weighting matrix, with similar results.

growth stocks (G) have slightly higher MKT betas than value stocks (V), but the difference is small. Similarly, there is little differential exposure to LVL shocks across book-to-market portfolios. The spread between value and growth risk premia entirely reflects differential compensation for CP risk. Value stocks have a large and positive exposure to CP shocks while growth stocks have a low exposure. The differential exposure between the fifth and first book-to-market portfolio is statistically different from zero. Multiplying the spread in exposures by the market price of CP risk delivers a value premium of 30 bps per month or 3.6% per year. That is, the CP factor's contribution to the risk premia accounts for most of the 4.1% value premium. Given the monotonically increasing pattern in exposures of the book-to-market portfolios to CP shocks, a positive price of CP risk estimate is what allows the model to match the value premium. Figure A.8 in the Appendix shows the same monotonically increasing pattern in exposures of book-to-market portfolio returns to innovations in the yield spread and in the yield factor that best predicts economic growth.

The top panel of Figure 5 shows the risk premium decomposition for the five bond portfolios. Risk premia are positive and increasing in maturity due to their exposure to LVL risk. The exposure to level shocks is negative and the price of level risk is negative, resulting in a positive contribution to the risk premium. This is the duration effect. But bonds also have a negative exposure to CP shocks. CP being a measure of the risk premium in bond markets, positive shocks to CP lower bond prices and realized returns. This effect is larger the longer the maturity of the bond. Given the positive price of CP risk, this exposure translates into an increasingly negative contribution to the risk premium. Because exposure of bond returns to the equity market shocks MKT is positive but near-zero, the sum of the level and CP contributions delivers the observed pattern of bond risk premia that increase in maturity.

One might be tempted to conclude that any model with three priced risk factors can always account for the three salient patterns in our test assets. To highlight that such a conjecture is false and to highlight the challenge in jointly pricing stocks and bonds, Appendix C gives a simple example where (1) the CP factor is a perfect univariate pricing factor for the book-to-market portfolios (it absorbs all cross-sectional variation), (2) the LVL factor is a perfect univariate pricing factor for the bond portfolios, and (3) the CP and the LVL factors are uncorrelated. It shows that such a model generally fails to price the stock and bond portfolios jointly. This failure arises because the bond portfolios are

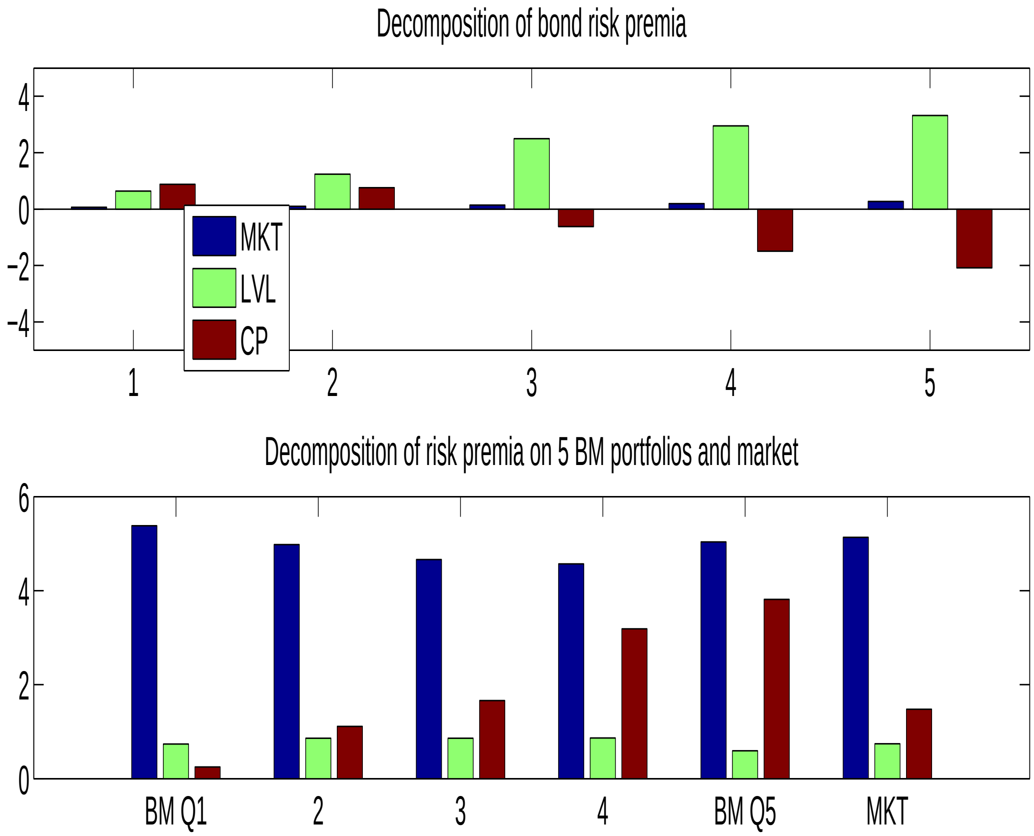

Figure 5: Decomposition of annualized excess returns in data.

The figure plots the risk premium (expected excess return) decomposition into risk compensation for exposure to the MKT, LVL, and CP factors. Risk premia, plotted against the left axis, are expressed in percent per year. The top panel is for the five bond portfolios: one-, two-, five-, seven-, and ten-year maturities from left to right, respectively. The bottom panel is for the book-to-market decile quintile portfolios, from growth (G) to value (V), and for the market portfolio (M). The three bars for each asset are computed as $\Sigma'_{XR}\Lambda_0$. The data are monthly from June 1952 until December 2012.

exposed to the CP factor, while the stock portfolios are not exposed to the LVL factor. Consistent risk pricing across stocks and bonds only works if the exposures of maturity-sorted bond portfolios to CP are linear in maturity, with the same slope (in absolute value) as the level exposures. The data happen to approximately satisfy the three assumptions underlying the stark model, but this is not a foregone conclusion. The example underscores the challenges in finding a model with consistent risk prices across stocks and bonds, or put differently, the challenge of going from univariate to multivariate pricing models.

To further quantify the separate roles of each of the three risk factors in accounting for the risk premia on these stock and bond portfolios, we return to columns (3)-(6) of Table 1. Column (3) of

Table 1 minimizes the pricing errors on the same 11 test assets but only allows for a non-zero price of level risk (Column *LVL*). This is the bond pricing model proposed by Cochrane and Piazzesi (2008). They show that the cross-section of average bond returns is well described by differences in exposure to the level factor. Long-horizon bonds have returns that are more sensitive to interest rate shocks than short-horizon bonds; a familiar duration argument. However, this bond SDF is unable to jointly explain the cross-section of stock and bond returns; the MAPE is 4.4%. All pricing errors on the stock portfolios are large and positive, there is a 4.4% value spread, and all pricing errors on the bond portfolios are large and negative. Clearly, exposure to the level factor alone does not account for the high equity risk premium nor the value risk premium. Value and growth stocks have similar exposure to the level factor, i.e., a similar "bond duration." The reason that this model does not do a better job at pricing the bond portfolios is that the estimation concentrates its efforts on reducing the pricing errors of stocks, whose excess returns are larger than those of the bonds.

To illustrate that this bond SDF is able to price the cross-section of bonds, we estimate the same model by minimizing only the bond pricing errors (the first five moments in Table 1). Column (4) of Table 1 (*LVL - only bonds*) confirms that the bond pricing errors fall substantially: The mean absolute bond pricing error goes from 208 bps in column 3 to 32 bps in column (4). However, the overall MAPE remains high at 4.05%. The canonical bond pricing model offers one important ingredient for the joint pricing of stocks and bonds, bonds' heterogeneous exposure to the level factor, but this ingredient does not help to account for equity returns.

Another benchmark is the model where the only non-zero price of risk is the one corresponding to the MKT factor. Column (5) of Table 1 (MKT) reports the corresponding pricing errors. Because past research has shown that the market factor cannot price book-to-market sorted stock portfolios, it is not surprising that this market model is also unable to jointly price stock and bond returns. The MAPE is 1.41%. One valuable feature is that the aggregate market portfolio is priced reasonably well and the pricing errors of book-to-market portfolio returns go through zero. Recall from our earlier discussion that our estimation procedure does not impose that the risk price on MKT equals its average return, explaining the small pricing error on the market portfolio itself of -1.33%. So, while the LVL factor helps to explain the cross-sectional variation in average bond returns and the MKT factor helps to explain the level of equity risk premia, neither factor is able to explain why value stocks have much higher risk premia than growth stocks. Column (6) of Table 1 indeed shows that having both the level and market factor priced does not materially improve the pricing errors and leaves the value premium puzzle in tact. Hence the need for the CP factor as a third priced asset pricing factor.

Column (7) in Table 1 reports results for a model that includes the market, SMB, and HML factors (Fama and French, 1992), which offers a better-performing alternative to the market model for pricing the cross-section of stocks. As discussed before, we do not impose the restriction that the risk prices equal the average returns on the factors. The model's MAPE is 63 bps per year. The slightly worse fit than that of the CP SDF model is due to higher pricing errors on the bond portfolios. Tests of the null hypothesis that all pricing errors are jointly zero are rejected at conventional levels.[13]

3.4 Pricing the Cross-section with a Traded CP Factor

Instead of using CP innovations as a pricing factor, we now construct a traded pricing factor that mimics CP innovations. We follow Malloy, Moskowitz, and Vissing-Jorgensen (2009) and regress CP innovations on a set of excess returns, R_t^e:

$$\epsilon_t^{CP} = \nu_0 + \nu_1' R_t^e + u_t. \tag{9}$$

We use the same estimation procedure to estimate the risk prices, but using $CP^T \equiv \nu_1' R_t^e$ as a pricing factor. We use four portfolios to mimic CP innovations that differ in terms of market capitalization and book-to-market ratio. Following Malloy et al. (2009), we construct a small value, a small growth, a large value, and a large growth portfolio from the standard 25 size- and book-to-market-sorted portfolios. For instance, to construct the small value portfolio, we take the bottom quintile in terms of size and average the two portfolios with the lowest book-to-market portfolios. We follow the same procedure for the other three portfolios. The replicating portfolio weights are given by $100 \times (\nu_1^{SG}, \nu_1^{SV}, \nu_1^{LG}, \nu_1^{LV})' = (-0.49, 2.08, -3.48, 2.69)$. The weights ν_1^{LV} and ν_1^{LG} are statistically

[13] We have verified that this rejection is due to the higher pricing errors on the bond moments. In unreported results, we find that the difference between the MAPE of our CP SDF model and the Fama-French model increases when we weight the 11 Euler equation errors by the inverse of their variance as opposed to equally. In addition, there remains a statistical difference between the p-values of chi-squared tests of the null that all pricing errors are jointly zero between our CP SDF model (5%) and the FF model (<1%) with the alternative weighting matrix. The reason is that our model fits the bond return moments better.

significant at the 5% level. The factor-mimicking portfolio goes long both value portfolios and shorts the growth portfolios, particularly large growth. We then replace CP innovations by CP^T as pricing factor and use it alongside the MKT and LVL factors.

Finally, column (8) of Table 1 demonstrates the ability of the traded CP^T factor to price the cross-section of stock and bond returns. Comparing the results to Column (2), the model with the traded CP factor prices stocks and bonds even better with a MAPE of only 24 bps per year. Ten out of eleven pricing errors are reduced in absolute value. The risk prices, as reported in Panel B, are comparable in both models. In particular, the market price of CP risk is 122 with the traded CP^T factor compared to 96 with CP innovations. They are not significantly different from each other. We continue to reject the null that all risk premia estimates are zero. With the traded CP factor, we do have more power to reject the model, although the MAPE are smaller. In summary, we can replace the non-traded CP factor with a traded factor that delivers similar results.

3.5 Adding Corporate Bond Portfolios

One asset class that deserves particular attention is corporate bonds. Stocks and corporate bonds are both claims on the firm's cash flows albeit with a different priority structure. We ask whether our SDF model is able to price portfolios of corporate bonds sorted by ratings class. Fama and French (1993) also include a set of corporate bond portfolios in their analysis. They conclude that a separate credit risk factor is needed to price these portfolios. In contrast, we find that the same three factors we used so far also do a good job pricing the cross-section of corporate bond portfolios, while providing an economic interpretation to the pricing factors.

The sample of corporate bond data starts only in 1980; the excess returns to be explained in this sample are listed in the first column of Table 2. We start by re-estimating our main results on this subsample. Column (2) shows that the MAPE on the 11 tests assets we considered in Section 3.3 is 44 bps, nearly identical to those in the full sample.[14] In terms of risk prices, we find a similar price of market risk, a more negative price of LVL risk, and a smaller price of CP risk. However, the risk

[14]In unreported results, we also studied the subsample 1963-2012, an often-used period for cross-sectional equity analysis (e.g., Fama and French, 1993). For that sample, the MAPE is 43 bps for the CP SDF. The p-value of the null hypothesis that all pricing errors are jointly zero is 5.7% for the CP SDF.

price estimates are not statistically different from their full sample values. The null hypothesis that all risk price estimates are zero is strongly rejected for both models. We fail to reject the null that all pricing errors are jointly zero.

The third column adds the pricing errors on the credit portfolios when we do not re-estimate the market prices of risk, but use those from Column 2. The model does a good job pricing the corporate bonds: mean absolute pricing errors on the credit portfolios are 73 bps per year, compared to excess returns of more than 4% per year under risk-neutral pricing. The mean absolute pricing error among all fifteen test assets is 52 bps per year in column 3; only 8 bps are added by the corporate bond portfolios.

Equally interesting is to re-estimate the market price of risk parameters of the SDF model when the corporate bond portfolios are included in the estimation. Column 4 shows that the corporate bond pricing errors now go through zero. For the CP SDF, the MAPE on the credit portfolios is 44 basis points per year and the overall MAPE on all 15 assets is 47 bps per year, 3 bps above the MAPE when corporate bonds are not considered, and 5 basis points less than when the corporate bonds were not included in the estimation. We fail to reject our model (p-value of 9.8%).

The last column of Table 2 reports results for the model with the MKT, SMB, and HML factors. Its pricing errors are higher than in our three-factor model; the MAPE is 93 bps. Average pricing errors on the corporate bond portfolios are 1% per year. The model severely underprices the BBB-rated portfolio (Credit4). Unlike our model, this model is rejected with a p-value of 0.9%.

4 Robustness

In this section, we confirm the robustness of our asset pricing results. We start by studying individual stocks sorted by their exposure to CP. We then consider other bond yield factors instead of CP. Third, we isolate business-cycle frequency dynamics. Fourth, we study bootstrap standard errors. Fifth, we consider additional sets of test assets.

Table 2: Unified SDF Model for Stocks, Treasuries, and Corporate Bonds

The table is similar to Table 1 except that the sample is January 1980 until December 2012. The table adds four corporate bond portfolios sorted by S&P credit rating: AAA (Credit1), AA, A, and BBB (Credit4). Their returns are expressed in percent per year. Column 2 excludes the credit portfolios in the estimation. Column 3 uses the market price of risk estimates of Column 2, and evaluates all pricing errors including those on the corporate bond portfolios. Column 4 includes the credit portfolios when estimating the risk prices.

	Panel A: Pricing Errors (% per year)				
	(1) RN SDF	(2)	(3) *CP* SDF not re-estim.	(4)	(5) MKT, SMB, HML
10-yr	3.91	0.22	0.22	0.58	-0.41
7-yr	3.80	0.15	0.15	0.51	0.29
5-yr	3.08	-0.15	-0.15	0.18	0.53
2-yr	1.86	-0.41	-0.41	-0.18	0.75
1-yr	1.27	-0.13	-0.13	0.02	0.78
Market	6.92	-0.96	-0.96	-0.99	0.86
BM1	6.76	-0.26	-0.26	-0.42	0.46
BM2	8.11	0.79	0.79	0.72	-1.01
BM3	7.57	0.24	0.24	0.21	-1.51
BM4	8.06	-0.68	-0.68	-0.47	-1.41
BM5	10.04	0.88	0.88	1.07	1.83
Credit1	3.40		-1.23	-0.80	0.43
Credit2	3.64		-0.95	-0.54	0.46
Credit3	4.12		-0.58	-0.19	1.06
Credit4	4.63		-0.14	0.23	2.10
MAPE	5.14	0.44	0.52	0.47	0.93
	Panel B: Prices of Risk Estimates				
MKT		2.20	2.20	2.31	6.77
LVL/SMB		-22.47	-22.47	-20.06	-22.54
CP/YSP/HML		51.47	51.47	45.81	2.53
	Panel C: P-values of chi-squared Tests				
$\Lambda_0 = 0$	–	1.19%	–	1.38%	0.61%
Pr. err. = 0	–	25.96%	–	9.75%	0.87%

4.1 Sorting stocks by CP-exposure

We investigate whether exposure to CP shocks is associated with higher equity risk premia in individual stocks. The exercise allows us to investigate whether the return spread on portfolios sorted by CP-exposure imply the same market price of CP risk as the one that we found in the previous section.

Our sample is the CRSP/Compustat universe between July 1963 and December 2010. For each stock-month pair, we regress excess returns on our pricing factors based on 60-month backward-looking rolling windows. If only a shorter history is available for a certain stock, we require at least 12 observations to estimate the CP beta. We start our first sort in June 1968. This ensures that we have 60 months of data for a substantial cross section of stocks to estimate the initial CP exposure more reliably. We sort stocks each year in June based on their CP beta and calculate the quintile portfolio returns over the next 12 months, value-weighting stocks within each portfolio.

We examine the returns of five portfolios sorted on their exposure to CP shocks in the previous 60 months. Table 3 reports a spread in average returns between the highest-CP exposure and the lowest-CP exposure portfolios of 2.4% per year. The standard CAPM cannot explain these portfolio returns. The spread in CAPM alphas is 2.4%, as high as the raw return spread. The MAPE of the CAPM for these CP-quintile portfolios is 82 bps per year. In contrast, our three-factor model *can* explain the return spread in the CP portfolios. The MAPE falls to 39 bps and the Q5-Q1 spread in the alphas with respect to our three factors (the "CP SDF alphas"), is only 0.5%.

Interestingly, the point estimate for the price of CP risk of 102 is quite close to that presented in our main estimation, even though we used no bond portfolios and different equity portfolios. The risk prices on the LVL factor equals -45 and that of the MKT is close to zero. Because the exposures of the CP-beta sorted portfolios to the LVL and MKT factors are similar across the five portfolios, the risk prices on these factors are hard to estimate separately. If we remove the LVL factor, we find that the risk price from CP hardly changes (from 102 to 97), but the price of MKT risk is now positive at 0.93 (last row of Table 3). Finally, we compute the covariances of the five portfolios with the CP factor and find that the difference between the high- and low-CP beta portfolios is positive. The positive risk price and positive spread in covariances allows our model to explain most of the spread in average returns between the CP portfolios.

Table 3: Individual Firm Returns: Single Sorts

This table reports the results of sorting individual firms into five portfolios based on their CP beta. We estimate the CP beta by regressing excess returns on the three pricing factors. We use 60-month rolling window estimates of CP betas, where we require at least 12 months of data for a stock to be included in one of the five portfolios. The table reports the average excess return per portfolio, the CAPM alphas, the alphas for our three-factor model ("CP SDF alphas"), the CP exposures of the five portfolios, the risk prices, and the mean absolute pricing error (MAPE) for the different models. The last row reports results for a version of our model where we omit the LVL factor; we do this because the exposures of the five portfolios to LVL and MKT are very similar. The data are monthly from July 1963 through December 2010.

	low CP Exposure	(2)	(3)	(4)	High CP Exposure	High-Low CP Exposure	Risk prices CP	LVL	MKT	MAPE
Avg. excess ret.	4.3%	4.9%	5.9%	5.8%	6.8%	2.4%				
CAPM alphas	-1.8%	-0.2%	1.0%	0.5%	0.6%	2.4%			2.07	82bp
CP SDF alphas	-0.2%	-0.3%	0.6%	-0.5%	0.4%	0.5%	102.22	-45.28	-0.15	39bp
CP covariances ($\times 10^5$)	2.30	2.13	1.96	2.95	3.60	1.30				
CP SDF alphas w/o LVL	-1.1%	0.1%	1.4%	0.0%	-0.2%	0.9%	96.6		0.93	56bp

Table A.VI in Appendix B also discusses an exercise where we double-sort stocks into quintiles based on their CP exposure and then, within CP quintile, on their book-to-market (BM) ratio. We find that our model eliminates substantial fraction of the return spreads and CAPM alphas along *both* CP and BM dimensions. In further support for our model, we find comparable market price of risk estimates to the benchmark ones.

4.2 Other Yield Curve Factors

The CP factor is a specific linear combination of one- through five-year bond yields that predicts economic activity and whose innovations have a monotonic covariance pattern with returns on the book-to-market portfolios. There are other linear combinations of the same five yields that may be better predictors of economic activity. Similarly, there may be other linear combinations of yields that do a better job pricing the cross-section of stock and bond returns. We consider three natural alternatives to CP. The first one is the slope of the yield curve, YSP, measured as the difference between the 5-year and the 1-year bond yields. The second one, YGR, is the linear combination of bond yields that best forecasts economic activity levels 12 months ahead as discussed above. The third one, YAP, is the linear combination of bond yields that best prices the 11 test assets over the full sample. The CP factor has a correlation of 73% with YSP, 58% with YGR, and 74% with YAP, while YSP has correlations of 69% with YGR and 30% with YAP. For ease of comparison, we rescale these three factors so they have the same standard deviation as CP. The predictability of CP for future economic activity, discussed in Section 2, extends to YSP and YGR as detailed in Appendix A, in particular Tables A.I and A.II. The predictability of YAP peaks at 21 months with R^2 of 8.5%. It is statistically significant predictor of $CFNAI$ for horizons ranging from 9 months to 27 months.

Next, we revisit the main asset pricing exercise with three alternative bond yield factors in lieu of the CP factor. Detailed results are in Table A.III in Appendix B. The model with the yield spread factor produces results broadly consistent with those for CP. It leads to a larger MAPE of 70 bps per year in the full sample, and leaves more of the value risk premium and the difference between long- and short-term bonds unexplained than the model with CP as a factor. The signs and approximate magnitude of the market prices of risk of YSP and CP are the same. When we add the corporate bond portfolios for the 1980-2012 sample, the MAPE falls further to 63 bps and we fail to reject the model.

The pricing model with YGR as the bond yield factor generates a MAPE of 59 bps for the full sample, 45 bps for the post-1980 sample, and 57 bps when we include the credit portfolios. In all three exercises, we cannot reject the model (p-values of 40%, 77%, and 36% respectively). The price of risk estimate for YGR in the main exercise is similar in magnitude and not statistically different from that of CP. These pricing results indicate that there is a lot of information about future economic growth in the term structure that is useful for pricing stocks and bonds. They also confirm that there is nothing special about CP for asset pricing beyond its ability to forecast economic growth.

Conversely, we find that we can lower MAPE to a mere 29 bps per year in the full sample by finding the best-pricing linear combination of 1- through 5-year bond yields. Using that same linear combination YAP, pricing errors are 33 bps for the post-1980 sample, and 44 bps for the same sample with credit portfolios. P-values for these three exercises are 25%, 33%, and 5%, respectively. The 74% correlation of CP with YAP helps explain why our main pricing results are strong. Both CP and YAP are earlier indicators of the cycle than YSP and YGR; they predict economic activity about two years out rather than about one year out. All these results are consistent with the view that there is an component in expected economic growth, as measured from the term structure of interest rates, that prices the joint cross-section of stock and bond returns.

4.3 Business-Cycle versus Long-Run Risk

To what extent do the term structure variables we study (CP, YSP, YGR) capture business cycle-frequency rather than lower-frequency risk? The evidence suggests the former. First, the growth predictability results are situated at horizons of 2-3 years which fall well within the range of business cycle frequencies (2 quarters to 5 years is a common definition). Second, all three term structure variables have annual persistence well below the persistence one would associate with long-run risk (0.50 for CP, 0.51 for the yield spread, and 0.19 for YGR). Third, we rule out that it is the low-frequency component of CP that is the one responsible for the asset pricing results. We construct a first pricing factor, $GDP1$, as the linear combination of yields that predicts 1-year GDP growth the best. Similarly, we find the linear combination of yields that predicts 5-year cumulative GDP growth the best and label it $GDP5$. We then regress $GDP1$ on $GDP5$ and label the residual of this regression as $GDP1-Ortho$. Because $GDP1-Ortho$ is orthogonal to $GDP5$, it isolates business-cycle frequency dynamics by construction. We show in Table A.IV of the Appendix that $GDP1$ (alongside the market and level factor) does a good job explaining the cross-section of stock and bond returns. The MAPE is 66 bps per year, consistent with our main results. If we use $GDP1 - Ortho$ instead of $GDP1$, the pricing performance *further improves*. The MAPE falls from 66 bps to 58 bps. Finally, $GDP5$ does not do nearly as well in pricing the cross-section of returns; the MAPE increases to 91 bps. Taken together, these results suggest that linear combinations of yields that predict near-term growth fare better in pricing the cross section of stock and bond returns than linear combinations of yields that predict long-term growth.

4.4 Bootstrap Exercise

To shed further light on the statistical significance of our asset pricing results, we perform a bootstrap analysis. The details are discussed in Appendix B.6. In short, we generate random bond yields with the same covariance structure and persistence as in the data and form the yield curve factors based on these generated yields. This allows us to take into account the estimation uncertainty coming from the fact that CP is a generated regressor. The exercise produces a p-value which indicates how likely we are to find our MAPE point estimate by chance. We focus on the results with the broadest cross-section of assets. We find a p-value of 3.5% for our CP SDF. The results show that the pricing results are unlikely to arise from chance alone. This is despite having three factors, two of which have non-trivial persistence, and despite having a strong factor structure in the test asset returns.

4.5 Other Test Assets

In addition to the credit portfolios discussed above, Appendix B considers several additional equity portfolios as test assets: 10 size-sorted portfolios, 10 earnings-to-price sorted portfolios, and 25 size and value double-sorted portfolios. Our three-factor model is able to reduce pricing errors on all of these sets of test assets substantially. We also discuss results using a different weighting matrix in the market price of risk estimation, which are very similar to our main results.

5 Conclusion

In this paper, we provide new evidence that the value premium reflects compensation for macroeconomic risk. Periods of low returns on value stocks versus growth stocks are times when future economic activity is low and future cash-flows on value stocks are low relative to those on growth stocks. We find that several bond market variables such as the Cochrane-Piazzesi (CP) factor and the slope of the yield curve are leading indicators of these business cycle turning points. Innovations to these factors are contemporaneously highly positively correlated with returns on value stocks, but uncorrelated with returns on growth stocks.

Based on this connection, we estimate a parsimonious three-factor pricing model that can be used to explain return differences between average excess returns on book-to-market sorted stock portfolios, the aggregate stock market portfolio, government bond portfolios sorted by maturity, and corporate bond portfolios. The first factor in our three-factor model is the traditional market return factor, the second one is the level of the term structure, and the third factor is the CP factor or the yield spread. We estimate a positive market price of risk for the latter risk factor, consistent with the notion that positive innovations represent good news about future economic activity.

Our results suggest that transitory shocks to the real economy operating at business cycle frequencies play a key role in accounting for the cross-section of stock returns. Future work on structural Dynamic Asset Pricing Models should bring the business cycle explicitly inside the model as a key state variable. The model solved in Appendix D is a starting point in this research agenda. More work is needed to help us fully understand why the market compensates exposure to innovations to this state variable so generously.

References

Ang, Andrew, and Geert Bekaert, 2007, Stock return predictability: Is it there?, *Review of Financial Studies* 20 (3), 651–707. 17

Baker, Malcolm, and Jeffrey Wurgler, 2012, Comovement and predictability relationships between bonds and the cross-section of stocks, *Review of Asset Pricing Studies* June. 5

Bakshi, Gurdip, and Zhiwu Chen, 2005, Stock valuation in dynamic economies, *Journal of Financial Markets* 8, 111–151. 4

Bansal, Ravi, and Bruce N. Lehman, 1997, Growth optimal portfolio restrictions on asset pricing models, *Macroeconomic Dynamics* 1, 333–354. 4

Bansal, Ravi, and Ivan Shaliastovich, 2010, A long-run risks explanation of predictability puzzles in bond and currency markets, Working Paper Duke University and the Wharton School. 4, 19

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset prizing puzzles, *The Journal of Finance* 59, 1481–1509. 4

Basu, Susanto, 1977, The investment performance of common stocks in relation to their price to earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, 663–82. 1

Bekaert, Geert, Eric Engstrom, and Steven Grenadier, 2010, Stock and bond returns with moody investors, *Journal of Empirical Finance* 17 (5), 867–894. 20

Bekaert, Geert, Eric Engstrom, and Yuhang Xing, 2009, Risk, uncertainty and asset prices, *Journal of Financial Economics* 91, 59–82. 4, 19

Binsbergen, Jules van, and Ralph Koijen, 2010, Predictive regressions: A present-value approach, *Journal of Finance* 65 (4). 6

Brennan, Michael J., Ashley W. Wang, and Yihong Xia, 2004, Estimation and test of a simple model of intertemporal capital asset pricing, *The Journal of Finance* 59 (4), 1743–1775. 5

Brooks, Jordan, 2011, Unspanned risk premia in the term structure of interest rates, Ph.D. thesis New York University. 9

Campbell, John, Adi Sunderam, and Luis Viceira, 2012, Inflation bets or deflation hedges? the changing risk of nominal bonds, Working Paper Harvard University. 4, 20, 26

Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251. 4

Campbell, John Y., Christopher Polk, and Tuomo Vuolteenaho, 2010, Growth or glamour? fundamentals and systematic risk in stock returns., *The Review of Financial Studies* 23(1), 305–344. 5

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Good beta, bad beta, *American Economic Review* 94(5), 1249–1275. 5

Chen, Long, 2009, On the reversal of return and dividend predictability: A tale of two periods, *Journal of Financial Economics* 92, 128–151. 8

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383–403. 4

Cochrane, John H., and Lars Peter Hansen, 1992, Asset pricing explorations for macroeconomics, in Olivier J. Blanchard, and Stanley Fischer, ed.: *NBER Macroeconomics Annual: 1992* . pp. 115–165 (MIT Press: Cambridge, MA). 4

Cochrane, John H., and Monika Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138–160. 1, 8, 17, 2, 10

———, 2008, Decomposing the yield curve, Working Paper, University of Chicago. 3, 24

Cooper, Ilan, and Richard Priestley, 2008, Time-varying risk premiums and the output gap, *Review of Financial Studies* 22, 2801–2833. 9

David, Alexander, and Pietro Veronesi, 2009, What ties return volatilities to price valuations and fundamentals?, Working Paper Chicago Booth. 20

De Bondt, Werner F.-M., and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793–805. 1

Duffie, Darrell, and Raymond Kan, 1996, A yield factor model of interest rates, *Mathematical Finance* 6, 379–406. 16

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465. 1, 17, 25

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56. 26

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, 385–415. 5

Gabaix, Xavier, 2012, Variable rare disasters: An exactly solved framework for ten puzzles in macro finance, *Quarterly Journal of Economics* 127(2), 645–700. 4

Gilchrist, Simon, and Egon Zakrajsek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* Forthcoming. 9

Hansen, Lars Peter, John C. Heaton, and Nan Li, 2008, Consumption strikes back? measuring long-run risk, *Journal of Political Economy* 116 (2), 260–302. 4, 6

Hansen, Lars Peter, and Ravi Jagannathan, 1997, Assessing specific errors in stochastic discount factor models, *Journal of Finance* 52, 557–590. 10

Joslin, Scott, Michael Priebsch, and Kenneth Singleton, 2010, Risk premiums in dynamic term structure models with unspanned macro risks, Working Paper Stanford University and MIT. 9

Kazemi, Hossein, 1992, An intertemporal model of asset prices in a markov economy with a limiting stationary distribution, *Review of Financial Studies* 5, 85–104. 4

Kung, Howard, 2014, Macroeconomic linkages between monetary policy and the term structure of interest rates, Working Paper UBC. 4

Lakonishok, Josef, Andrei Schleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *The Journal of Finance* 49 (5), 1541–1578. 1

Larrain, Borja, and Motohiro Yogo, 2007, Does firm value move too much to be justified by subsequent changes in cash flow?, *Journal of Financial Economics* 87(1), 200–226. 6

Lettau, Martin, and Jessica Wachter, 2007, Why is long-horizon equity less risky? a duration-based explanationof the value premium, *Journal of Finance* 65, 55–92. 1

———, 2009, The term structures of equity and interest rates, Working Paper University of Pennsylvania Wharton School. 4, 20, 27

Lewellen, Jonathan, Jay Shanken, and Stefan Nagel, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194. 13

Ludvigson, Sydney, and Serena Ng, 2009, Macro factors in bond risk premia, *Forthcoming Review of Financial Studies*. 9

Lustig, Hanno, Stijn Van Nieuwerburgh, and Adrien Verdelhan, 2013, The wealth-consumption ratio, *Review of Asset Pricing Studies* 3(1), 38–94. Review of Asset Pricing Studies. 4

Malloy, Chris, Tobias Moskowitz, and Annette Vissing-Jorgensen, 2009, Long-run stockholder consumption risk and asset returns, *Journal of Finance* forthcoming. 25

Menzly, Lior, Tano Santos, and Pietro Veronesi, 2004, Understanding predictability, *Journal of Political Economy* 112, 1–47. 4

Petkova, Ralitsa, 2006, Do the fama-french factors proxy for innovations in predictive variables?, *Journal of Finance* 61(2), 581–612. 5

Piazzesi, Monika, and Martin Schneider, 2006, Equilibrium yield curves, *National Bureau of Economic Analysis Macroeconomics Annual*. 4

Santos, Jesus, and Pietro Veronesi, 2010, Habit formation, the cross-section of stock returns and the cash flow risk puzzle, *Journal of Financial Economics* 98, 385–413. 4

Wachter, Jessica, 2006, A consumption-based model of the term structure of interest rates, *Journal of Financial Economics* 79, 365–399. 4, 19

Yoon, Pyung Sig, and Laura T. Starks, 1995, Signaling, investment opportunities, and dividend annoucements, *Review of Financial Studies* 8 (4), 995–1018. 8

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60 (1), 67–103. 1, 4

Appendix

A. Additional Results for Section 2

A.1. Dividends Around NBER Recessions pre-1952

The main text shows the behavior of log annual real dividends on value (fifth book-to-market), growth (first book-to-market), and market portfolios for the sample 1952-2012 in the left panel of Figure 1 as well as the difference in dividend growth between value and growth portfolios in the right panel of Figure 1. Figure A.1 shows the corresponding evidence for the period 1926 until 1952. The message of these figures is very much consistent with the discussion in the main text. The massive decline in dividends of value stocks relative to that of dividends of growth stocks in the Great depression is noteworthy.

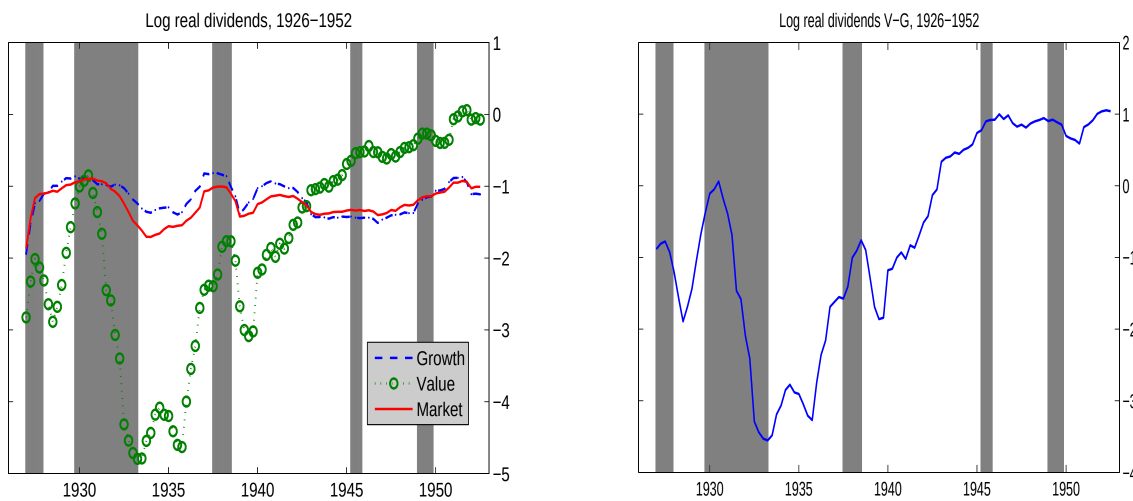

Figure A.1: Dividends on value, growth, and market portfolios pre-1952.

The left panel plots the log real dividend on book-to-market quintile portfolios 1 (growth, dashed line with squares) and 5 (value, dotted line with circles) and on the CRSP value-weighted market portfolio. The right panel plots the log real dividend on book-to-market quintile portfolios 5 (value) minus the log real dividend on the boot-to-market portfolio 1 (growth). Dividends are constructed form cum- and ex-dividend returns on these portfolios. Monthly dividends are annualized by summing dividends received during the year. The data are monthly from December 1926 until June 1952 and are sampled every three months in the figure.

A.2. Predicting economic activity and dividend growth

Table A.I reports the slopes of time series predictability regressions of the form

$$y_{t+k} = c_k + \beta_k Z_t + \varepsilon_{t+k}, \tag{A.1}$$

where Z_t is one of three different bond factors and y is one of three measures of economic growth. The left three columns (Panel A) use the economic activity measure $CFNAI$ as the outcome variable. The bond factor is the CP factor in the first column, the slope of the yield curve YSP in the second column, and the linear combination of bond yields that best forecasts CFNAI 12 months ahead, YGR, in the third columns. For ease of comparability, YSP and YGR have been rescaled to have the same standard deviation as CP. The next three columns (Panel B) use dividend growth on the market portfolio as outcome variable y. The last three columns (Panel C) use the difference between dividend growth

Table A.I: Predicting economic activity and dividend growth

This table reports slope coefficients from predictive regressions. The predictors Z are listed in the first row. They are the CP factor, the yield spread YSP, and the best linear forecaster of $CFNAI_{t+12}$, YGR. The forecast horizon is listed in the first column. All predictors have the same standard deviation over the sample so that the slope coefficients within each panel are directly comparable. In Panel A, the bond market variables forecast $CFNAI$. In Panel B, they forecast real dividend growth on the market portfolio. In Panel C, they forecast dividend growth on the value minus the growth portfolio. The data are monthly from March 1967 through December 2012. Numbers in bold have Newey-West t-statistics in excess of 1.96.

	CP	YSP	YGR	CP	YSP	YGR	CP	YSP	YGR
k	Panel A: CFNAI			Panel B: Div. Growth M			Panel C: Div. Growth $V-G$		
12	**18.16**	**19.56**	**27.35**	0.59	**1.09**	0.40	-1.97	-2.29	-1.89
15	**21.93**	**19.70**	**25.42**	**0.94**	**1.43**	0.64	-0.24	0.29	0.46
18	**23.87**	**20.56**	**23.84**	**1.13**	**1.68**	**0.87**	1.08	2.42	2.06
21	**24.87**	**18.90**	**16.80**	**1.28**	**1.86**	**1.09**	2.15	4.11	3.46
24	**21.39**	**14.52**	10.52	**1.31**	**1.96**	**1.22**	3.02	**5.32**	**4.39**
27	**18.22**	12.06	7.93	**1.32**	**2.00**	**1.26**	3.51	**5.65**	**4.62**
30	**14.70**	8.87	4.86	**1.54**	**2.14**	**1.36**	3.90	**5.64**	4.39
33	12.30	5.92	1.90	**1.62**	**2.17**	**1.34**	**4.62**	**5.52**	3.53
36	7.56	2.38	-1.44	**1.60**	**2.04**	**1.14**	**5.14**	5.23	2.71

on the value portfolio (fifth book-to-market quintile portfolio) and the growth portfolio (first book-to-market quintile) as the y variable. Figure 2 in the main text contains a visual representation of the results with CP as predictor.

YGR, in the third column, has the highest possible slope coefficient (27.4), t-statistic (4.9), and R^2 at the 12-month forecast horizon (18.5%) by construction. The predictive ability of YGR deteriorates with the horizon. At 24 months, the slope is 10.5 and the point estimate is no longer significantly different from zero. The yield spread, in the second column, is a slightly stronger predictor of economic activity 12 months out (slope of 19.6) than CP (slope of 18.2), but the R^2 values are about half of those for the best linear combination of yields (10.9% and 7.9%, respectively). The predictability of YSP peaks at 18 months, with a slope of 20.6, a t-stat of 3.7, and an R^2 of 10.5%. The predictability is statistically significant for horizons from 2 months to 25 months. After that same 24-month horizon, YSP also loses its predictive ability. The CP factor, in contrast, is a much stronger predictor than YSP or YGR 24 months out. In fact, CP is close to the best linear predictor at that 24-month horizon.

Panel B shows that both CP and YSP predict future dividend growth on the market significantly at (nearly) all horizons. YGR predicts future dividend growth at horizons beyond 18 months. In terms of size of the coefficient and R-squared, YSP has the strongest predictive ability and YGR the weakest, with CP in between. Panel C shows that all three measures have some predictive ability for the relative dividend growth on value minus growth stocks. The predictive ability of CP is concentrated at horizons of 33-36 months, that of YSP at horizons of 24-33 months, and that of YGR at horizons of 24-27 months.

A.3. Predicting GDP growth with CP

In the main text we show that the bond factors Z forecast future economic activity, as measured by the $CFNAI$ index. As an alternative to $CFNAI$, we consider real gross domestic product (GDP) growth (seasonally adjusted annual rates) from the National Income and Product Accounts. The GDP data are available only at quarterly frequency, but go back to 1952 when the CP series starts. This gives us a longer sample than for CFNAI, which starts in 1967. When $Z = CP$, our results update a regression that appears in the working paper version of Cochrane and Piazzesi (2005). The yield factor Z in a given quarter is set equal to the value in the last month of the quarter. We estimate

$$\Delta GDP_{t+k} = c_k + \beta_k Z_t + \varepsilon_{t+k}, \tag{A.2}$$

Table A.II: Predicting quarterly $CFNAI$ and GDP Growth

This table reports slope coefficients from predictive regressions. The predictors Z are listed in the first row. They are the CP factor, the yield spread YSP, and the best linear forecaster of real GDP growth 5 quarters ahead, $YGDP$. The forecast horizon is listed in the first column. All predictors have the same standard deviation over the sample so that the slope coefficients within each panel are directly comparable. In Panel A, the bond market variables forecast $CFNAI$ (last month of the quarter). In Panel B, they forecast real four-quarter GDP growth, measured quarterly. The data in Panel A are quarterly for 1967.I through 2012.IV while the data in Panel B are quarterly for 1952.III until 2012.IV.

	CP	YSP	$YGDP$	CP	YSP	$YGDP$
k	Panel A: $CFNAI$			Panel B: GDP Growth		
4	**15.60**	**18.88**	**29.85**	**0.33**	**0.47**	**0.72**
5	**19.35**	**19.74**	**31.21**	**0.38**	**0.50**	**0.77**
6	**25.56**	**20.26**	**25.93**	**0.37**	**0.44**	**0.68**
7	**28.81**	**20.38**	**19.67**	**0.40**	**0.39**	**0.58**
8	**25.19**	**16.51**	10.43	**0.42**	**0.34**	**0.46**
9	**22.45**	13.81	7.58	**0.37**	0.23	0.24
10	**20.06**	11.71	4.29	0.34	0.17	0.14
11	**17.74**	8.85	0.82	0.29	0.09	0.02
12	11.14	4.49	-4.00	0.22	0.03	0.00

where k is the forecast horizon expressed in quarters. Table A.II shows the coefficient estimates β_k in Panel B. For comparison, Panel A predicts $CFNAI$ with the same variables using the same quarterly frequency. $CFNAI$ then refers to the last month of the quarter. The predictors have been scaled to have the same standard deviation within each sample so that the point estimates are directly comparable for different predictors Z. In addition to CP and YSP, we also consider the best linear forecaster of GDP growth 5 quarters out, the horizon over which we get the highest overall predictability. We call this yield curve predictor $YGDP$.

We find that all three predictors strongly forecast annual GDP growth 4 to 8 quarters ahead. That is, they predict GDP growth over the following year and over the year thereafter. The yield spread YSP is again a stronger predictor at shorter horizons while CP is a stronger predictor at longer horizons. CP predicts GDP growth at longer horizons even better than $YGDP$. The R^2 value for CP (YSP) at $k = 5$ quarters is 5.5% (9.6%), compared to 22.1% for $YGDP$, the theoretical maximum. At $k = 8$ quarters, the R^2 value for CP (YSP) is 6.9% (4.4%), compared to 8.4% for $YGDP$. For longer horizons, CP has the highest R^2. All variables lose statistical significance for horizons of 10 quarters or more. The results in Panel A confirm what we learned in the main text: CP predicts economic activity strongly, and more strongly so at longer horizons. The YSP predicts $CFNAI$ about as well as $YGDP$ at intermediate horizons.

A.4. CP, YSP, and NBER Recessions

Figure A.2 plots the CP and YSP factors over time (right axis) while drawing in NBER recessions (shaded areas). Consistent with the economic forecasting regressions, the CP and YSP factors are low before the start of most recessions in the post-1952 sample. They subsequently increases over the course of a recession, especially towards the end of the recession when better times are around the corner. In nearly every recession, the CP and YSP factors are substantially higher at the end than at the beginning of the recession. In the three deepest post-war recessions, the 1974, 1982, and 2008 recessions, CP dips in the middle of the recession -suggesting that bond markets fear a future deterioration of future economic prospects- before recovering.

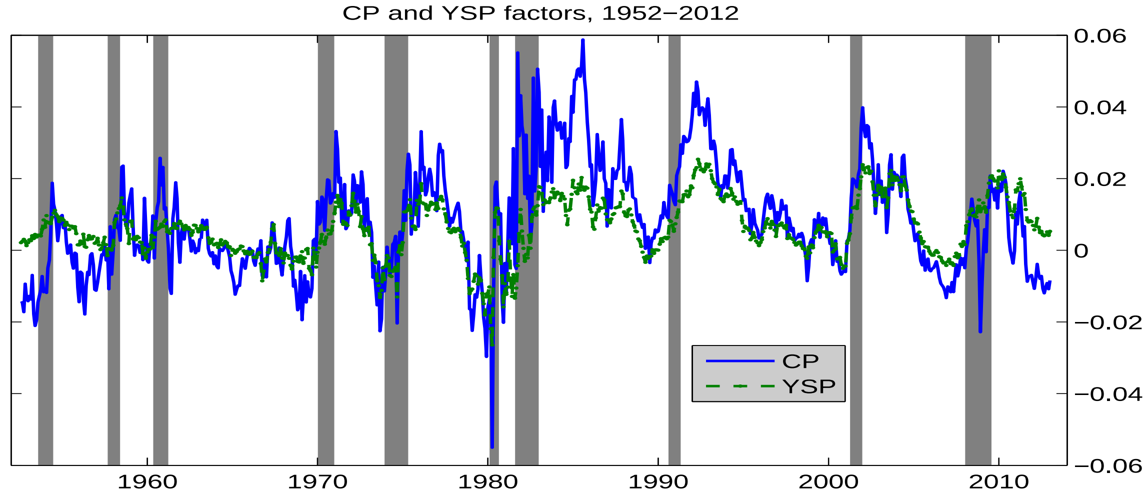

Figure A.2: CP factor and NBER recessions.

The figure plots the CP factor (solid line, against the right axis) and the NBER recessions (shaded areas). The sample is July 1952 until December 2011.

A.5. Real GDP in CP-event Time

We also study the behavior of real annual GDP growth in CP-event time. GDP growth rates are available over the entire post-war sample, whereas $CFNAI$ only starts in 1967. Figure A.3 is the same as Figure 3 in the main text, except that real GDP growth is plotted in the bottom right-hand side panel instead of $CFNAI$. Like $CFNAI$, GDP growth also shows a clean cycle around low-CP events. GDP grows at a rate that is 1.3% point above average two quarters before the event, the growth rate slows down to 0.6% points above the average in the event quarter, and growth further falls to a rate of 1.8% points below average five quarters after the event. The amplitude of this cycle (3.1% points) is economically large, representing 1.24 standard deviations of GDP growth.

A.6. Low-YSP Events

Figure A.4 is the same as Figure 3 in the main text, except that we condition on low realizations of the yield spread rather than low realizations of the CP factor. Like the CP factor, the yield spread first falls towards period 0 and later increases. Economic activity (and also GDP growth, not shown) fall following the low YSP event, consistent with the predictability evidence. Also, dividend growth on value minus growth falls, but with a substantial lag.

A.7. One-factor Model

One may wonder whether the facts our paper documents are consistent with a one-factor model that differentially affects cash flow growth rates and therefore returns on value versus growth stocks. The data suggest that they are not. An adequate description of dividend dynamics contains at least two shocks: one shock that equally affects dividend growth rates on all portfolios and a second shock (to the Z factor) that affects value dividends relative to growth dividends.

To see this, we orthogonalize value-minus-growth dividend growth to the dividend growth rate on the market portfolio. Figure A.5 compares the dynamics of dividend growth on value minus growth around low-CP events (left panel, which repeats the bottom left panel of Figure 3) to those of dividend growth on the market portfolio (middle panel), and of the orthogonal component of value-minus-growth dividend growth (right panel). All three dividend

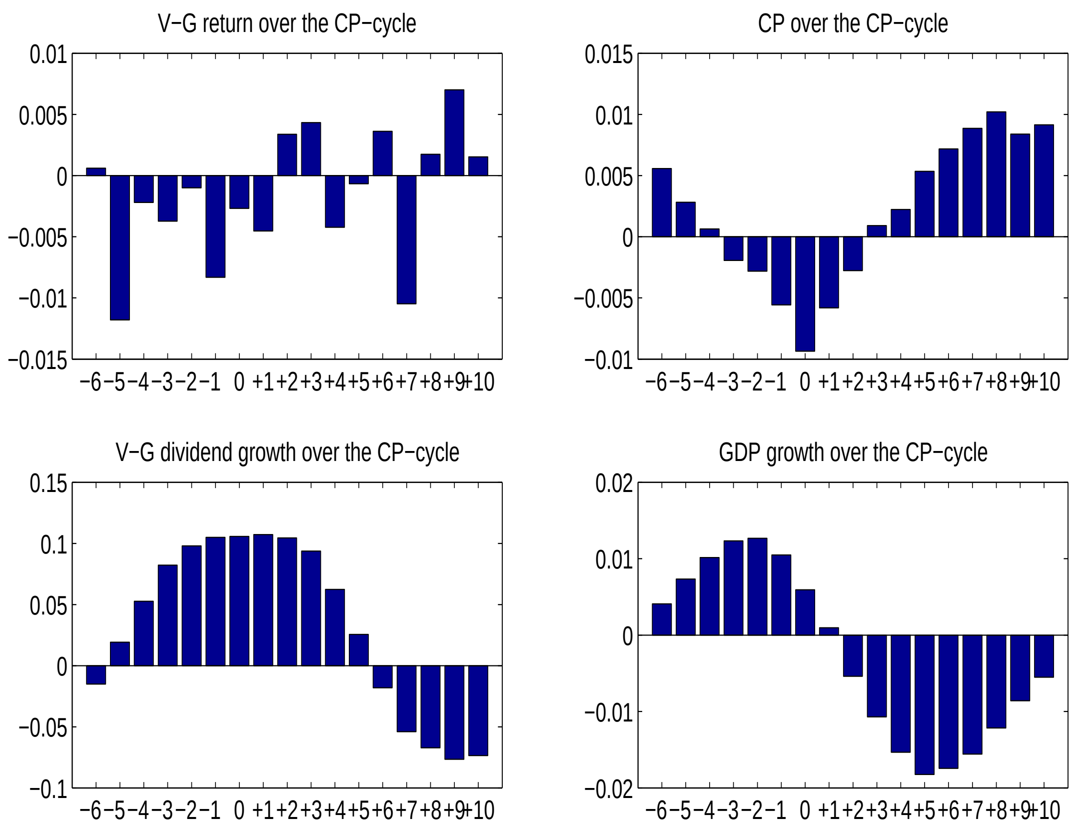

Figure A.3: Low-CP events with GDP growth

The figure plots four quarterly series in event time. The event is defined as a quarter in which the quarterly CP factor in its respective lowest 25% of observations. This selection leads to 60 events out of 242 quarters. The sample runs from 1953.III until 2012.IV. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The top left panel plots the realization of the quarterly log return on value minus growth. The bottom left panel reports annual log dividend growth on value minus growth. The top right panel plots the CP factor. The bottom right panel plots real GDP growth. Real GDP growth is demeaned over the full sample.

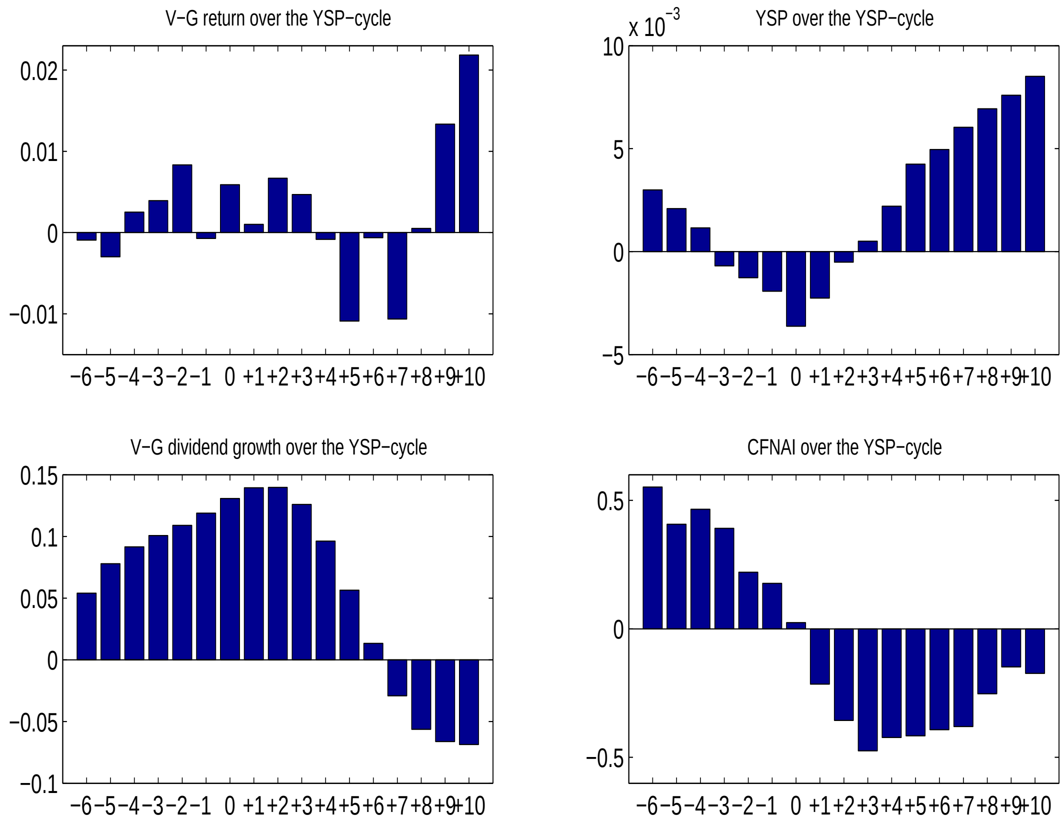

Figure A.4: Low YSP Events

The figure plots four quarterly series in event time. The event is defined as a quarter in which the quarterly YSP factor in its respective lowest 25% of observations. This selection leads to 60 events out of 242 quarters. The sample runs from 1953.III until 2012.IV. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The top left panel plots the realization of the quarterly log return on value minus growth. The bottom left panel reports annual log dividend growth on value minus growth. The top right panel plots the YSP factor. The bottom right panel plots the $CFNAI$ index of economic activity. The latter is available only from 1967.II onwards. Formally, the graph reports $c_k + \beta_k$ from a regression $X_{t+k} = c_k + \beta_k \mathcal{I}_{YSP_t<LB} + \epsilon_{t+k}$, for various k, where $\mathcal{I}$ is an indicator variable, LB is the 25th percentile of YSP, and X is the dependent variable which differs in each of the four panels. Value-minus growth returns and value-minus-growth dividend growth have been demeaned over the full sample; $CFNAI$ is also mean zero by construction.

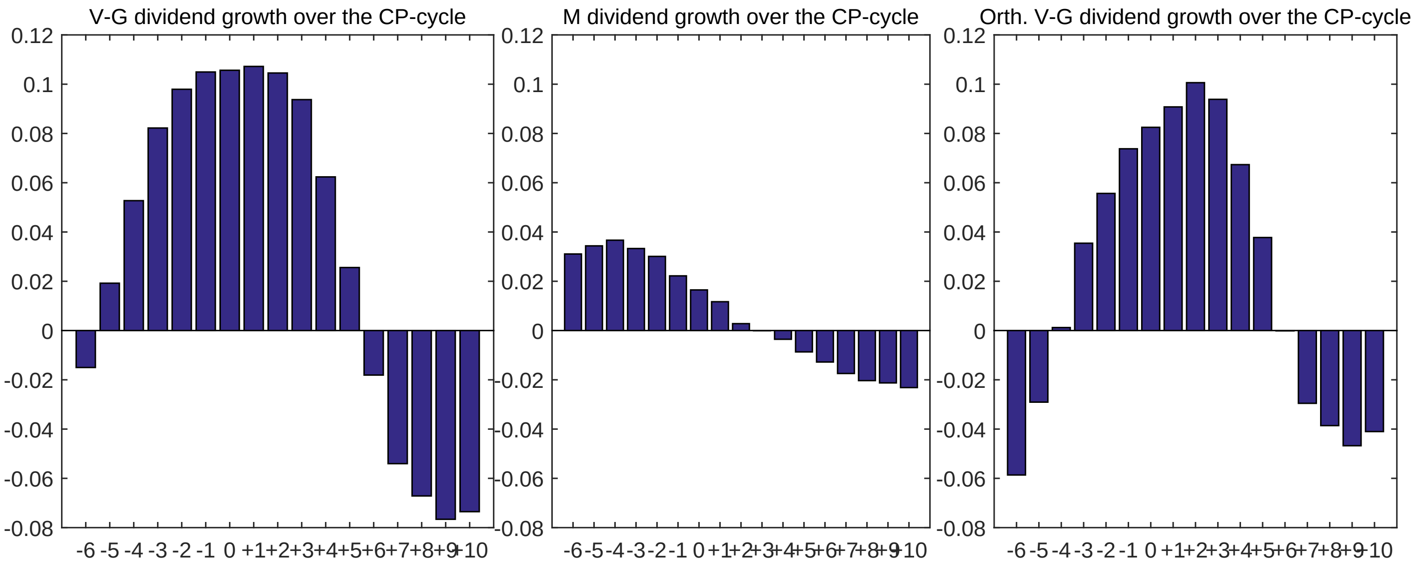

Figure A.5: Dividend growth around Low-CP events

The figure plots three quarterly series in event time. The event is defined as a quarter in which the quarterly CP factor in its respective lowest 25% of observations. This selection leads to 60 events out of 242 quarters. The sample runs from 1953.Q3 until 2012.Q4. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The left panel plots annual log dividend growth on value minus growth, the middle panel plots annual log dividend growth on the market portfolio, and the right panel plots annual log dividend growth on value minus growth, orthogonalized to annual log dividend growth on the market portfolio. All three series have mean-zero over the full sample.

growth series are demeaned over the full sample. The figure shows that the dividend growth on the market portfolio falls in the aftermath of a low-CP event, consistent with the facts on aggregate economic activity or GDP growth. The dividend growth rate on the market portfolio falls by 3.7% in the ten quarters following the CP events. This is however a much smaller effect than the 19.9% point decline in value-minus-growth dividend growth. Furthermore, the part of value-minus-growth dividend growth that is orthogonal to the market dividend growth, in the right panel, has qualitatively and quantitatively similar dynamics around CP events as the raw value-minus-growth dividend growth in the left panel. It falls by 14.7% points in the ten quarters following an average low-CP event. The R^2 of the regression of value-minus-growth dividend growth rate on the market dividend growth rate is only 14%, leaving a lot of the dynamics in dividend growth on value-minus-growth unaccounted for by dividend growth on the market portfolio.

There are several other reasons why our facts are inconsistent with a simple one-factor model, such as the CAPM. First, we can orthogonalize the CP factor to the excess market portfolio return. The orthogonal component of CP predicts dividend growth on value-minus-growth as well as the raw CP series does. The reason is that the CP factor is nearly orthogonal to the excess stock market return; the R^2 of the orthogonalization regression is 2%. Second, low-CP events do not coincide with periods of low aggregate stock market returns. Third, the evidence is inconsistent with a conditional tail-beta explanation. In periods of low market returns, the conditional beta of value stocks is lower than that of growth stocks. The theoretical model of Appendix D articulates this two-shock structure of cash flow growth. It features a common and permanent cash-flow shock that affects all portfolios alike, and a business-cycle frequency shock that differentially affects dividend growth rates of value and growth stocks.

A.8. Real GDP and YSP around Low-value Events

Figure A.6 shows the analogous figure to Figure 4 in the main text, except that real GDP growth is plotted in the bottom right-hand side panel instead of $CFNAI$ and the yield spread YSP is plotted in the top right-hand side panel instead of CP. GDP growth is demeaned over the full sample. GDP growth is only modestly below average in period

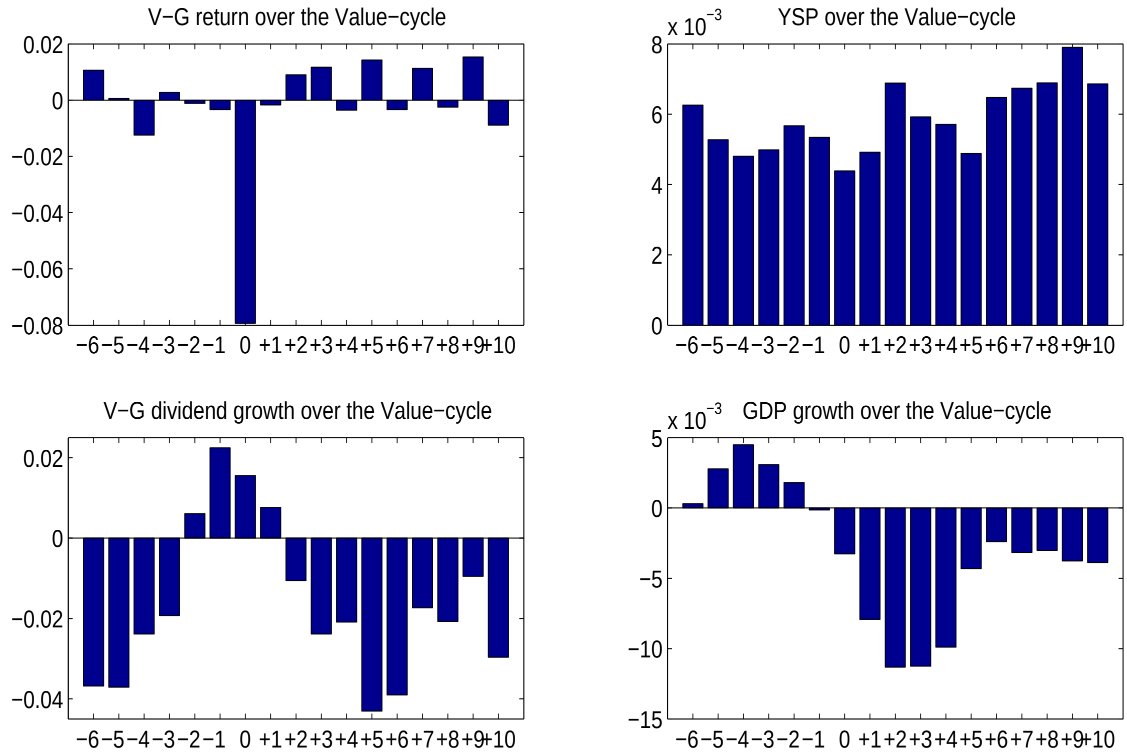

Figure A.6: Low-value Events

The figure plots four quarterly series in event time. The event is defined as a quarter in which both the realized log real return on the fifth book-to-market portfolio (value) and the realized log return on value minus growth (first book-to-market portfolio) are in their respective lowest 30% of observations. This intersection leads to 37 events out of 242 quarters (15%). The sample runs from 1953.III until 2012.IV. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The top left panel plots the realization of the quarterly log return on value minus growth. The bottom left panel reports annual log dividend growth on value minus growth. The top right panel plots the slope of the yield curve (YSP). The bottom right panel plots real GDP growth. Real GDP growth is demeaned over the full sample.

0 (-0.33% points), but falls to -1.1% points below average two-to-three quarters after the event. The change from 4 quarters before to 3 quarters after is 1.6% points, which is almost two-thirds of a standard deviation of real GDP growth. Like CP, the yield spread YSP shows a v-shaped pattern around the low-value event, consistent with innovations to the YSP being positively correlated with low value returns.

A.9. Dividend Growth Rates around Low-value Events

Figure A.7 compares the dynamics of dividend growth on value minus growth around value crash events (left panel, repeats the bottom left panel of Figure 4 in the main text) to the dynamics of dividend growth on the market portfolio (middle panel), and the part of value-minus-growth dividend growth that is orthogonal to market dividend growth rates (right panel). All three dividend growth series are demeaned over the full sample. The figure shows that (a) the dividend growth on the market portfolio falls in the aftermath of a low-CP event, consistent with the facts on aggregate economic activity or GDP growth, (b) that this effect is much smaller than that on value-minus-growth dividend growth, and (c) that the part of value-minus-growth dividend growth that is orthogonal to the market dividend growth, in the right panel, has qualitatively and quantitatively similar dynamics around low-value events as the raw value-minus-growth dividend growth in the left panel.

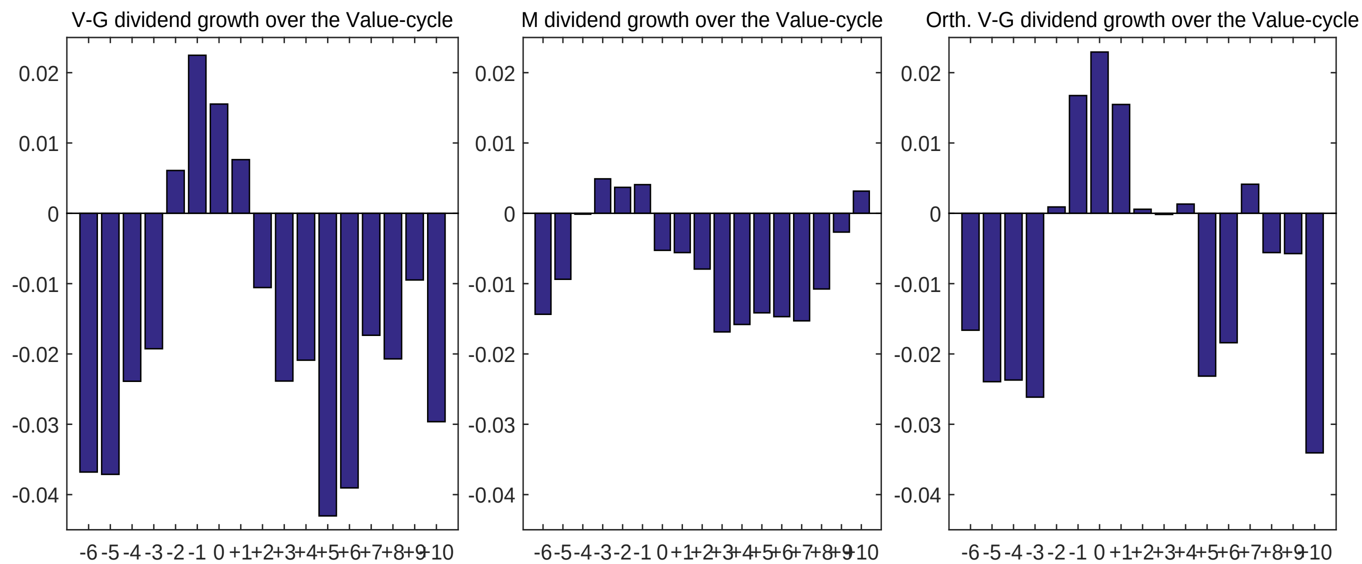

Figure A.7: Dividend Growth Around Low-value Events

The figure plots three quarterly series in event time. The event is defined as a quarter in which both the realized log real return on the fifth book-to-market portfolio (value) and the realized log return on value minus growth (first book-to-market portfolio) are in their respective lowest 30% of observations. This intersection leads to 35 events out of 238 quarters (15%). The sample runs from 1953.Q3 until 2011.Q4. In each panel, the period labeled '0' is the quarter in which the event takes place. The labels -1, -2, -3, etc refer to one, two, three, etc quarters before the event whereas the labels +1, +2, +3, etc. refer to one, two, three, etc quarters after the event. The left panel plots annual log dividend growth on value minus growth, the middle panel plots annual log dividend growth on the market portfolio, and the right panel plots annual log dividend growth on value minus growth, orthogonalized to annual log dividend growth on the market portfolio.

B. Additional Results for Section 3

This section considers several exercises investigating the robustness of our empirical results in Section 3. First, we provide details on the estimation of the time-varying component of the market prices of risk. Second, we we use a different weighting matrix in the market price of risk estimation. Third, we show exposures of boot-to-market portfolio returns to innovations in three bond yield factors. Fourth, we redo the main asset pricing results for three alternative yield spread factors. Fifth, we study additional sets of test assets. Sixth, we provide detailed results for the stock-level exercise.

B.1. Time-varying Risk Prices

Having estimated the constant market prices of risk, Λ_0, we turn to the estimation of the matrix Λ_1, which governs the time variation in the prices of risk. We allow the price of level risk $\Lambda_{1(2)}$ and the price of market risk $\Lambda_{1(3)}$ to depend on the Z factor, where Z is CP, YSP, YGR, or YAP. We use two predictive regressions to pin down this variation in risk prices. We regress excess returns on a constant and lagged Z:

$$rx_{t+1}^{j} = a_j + b_j Z_t + \eta_{t+1}^{j},$$

where we use either excess returns on the stock market portfolio or an equally-weighted portfolio of all bond returns used in estimation. Using equation (5), it then follows:

$$\begin{pmatrix} \Lambda_{1(2)} \\ \Lambda_{1(3)} \end{pmatrix} = \begin{pmatrix} \Sigma_{X,Market(2:3)} \\ \Sigma_{X,Bonds(2:3)} \end{pmatrix}^{-1} \times \begin{pmatrix} b_{Market} \\ b_{Bonds} \end{pmatrix}.$$

Following this procedure in the full sample, we find $\hat{\Lambda}_{1(2)} = -890$ and $\hat{\Lambda}_{1(3)} = 44$ when $Z = CP$. This implies that equity and bond risk premia are high when CP is high, consistent with the findings of Cochrane and Piazzesi (2005). We find similar results with $\hat{\Lambda}_{1(2)} = -736$ and $\hat{\Lambda}_{1(3)} = 115$ when $Z = YSP$.

B.2. Weighted Least-Squares

Our cross-sectional estimation results in Table 1 assume a GMM weighting matrix equal to the identity matrix. This is equivalent to minimizing the root mean-squared pricing error across the 11 test assets. The estimation devotes equal attention to each pricing error and leads to a RMSE of 48bp per year. A natural alternative to the identity weighting matrix is to give more weight to the assets that are more precisely measured. We use the inverse covariance matrix of excess returns, as in Hansen and Jagannathan (1997). This amounts to weighting the bond pricing errors more heavily than the stock portfolio pricing errors in our context. When using the Hansen-Jagannathan distance matrix, we find a MAPE of 53bp per year compared to 41bp per year. However, the weighted RMSE drops from 48bp to 25bp per year. The reason for the improvement in RMSE is that the pricing errors on the bonds decrease substantially, from a MAPE of 43bp to 12bp per year. Finally, the price of risk estimates in $\hat{\Lambda}_0$ are comparable to those in the benchmark case. The price of CP risk remains positive and is estimated to be somewhat lower than in the benchmark case, at 48.3 (with a standard error of 12.2). The market price of LVL risk remains statistically negative (-14.7 with standard error of 6.3), and the price of MKT risk remains positive (2.67 with a standard error of 1.1). The null hypothesis that all pricing error parameters are jointly zero continues to be strongly rejected. We conclude that our results are similar when we use a different weighting matrix.

B.3. Bond Factors Are Priced

Figure A.8 shows covariances between unexpected returns on each of the quintile book-to-market portfolios, ordered from growth (low B/M) to value (high B/M), with innovations to the three bond factors. The monotonically increasing pattern in exposures will generate a value premium if the price of risk associated with innovations in the bond factors is positive. Standard ICAPM logic implies that this price of risk is positive provided that innovations to the factors lower the marginal utility of wealth for the average investor. This is natural because innovations to CP, YSP, and YGR represent good news about future economic performance. Indeed, all are strong predictors of the level of economic activity 12 to 24 months ahead, as we saw before.

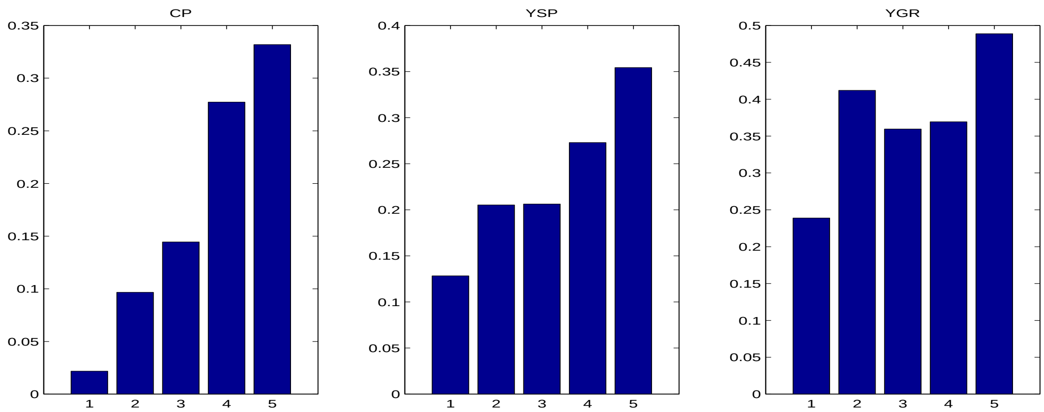

Figure A.8: Exposure of value and growth portfolio returns to bond risk premium innovations.

The figure shows the covariance of innovations to returns on five quintile portfolios sorted on the book-to-market ratio with innovations to three bond market factors. In the left panel, the bond factor is the Cochrane and Piazzesi (CP) factor. In the middle panel, it is the yield spread (YSP). In the right panel, it is the bond factor that maximally predicts economic activity $CFNAI$ twelve months out (YGR). Innovations to bond factors and returns are described in detail in Section 3. On the horizontal axes, Portfolio 1 denotes the lowest book-to-market (growth) portfolio; portfolio 5 is the highest book-to-market (value) portfolio. The covariances are multiplied by 10,000. The sample is monthly from June 1952 until December 2012.

B.4. Asset Pricing with Other Bond Yield Factors

We revisit the main asset pricing exercise with three alternative bond yield factors in lieu of the CP factor. That is, we replace CP by YSP, YGR, or YAP in the VAR, form innovations and use the resulting three-dimensional VAR innovation vector to price the cross-section of maturity-sorted government bond portfolios, the value-weighted stock market, boom-to-market sorted equity portfolios, and four credit-quality sorted bond portfolios.

The first three columns of Table A.III show the results when we use the slope of the yield curve YSP in lieu of CP. The pricing errors and market prices of risk are qualitatively similar to the ones reported in the main text with the CP factor. The model with the yield spread leads to a larger MAPE of 70 bps per year in the full sample, and leaves more of the value risk premium and the difference between long- and short-term bonds unexplained than the model with CP as a factor. The signs on the market prices of risk are the same, with a large positive price of risk estimate for YSP of 100.1, close to the one for CP in column 2. For comparability of the market prices of risk, YSP is normalized so that it has the same standard deviation as CP over the estimation sample. (This makes little difference because their standard deviations are close.) The market price of YSP risk is strongly significant, with a standard error of 31.9 (t-statistic = 3.1). The MKT factor has a t-statistic of 2.1 but the LVL factor is insignificant (t-stat = -0.6). The null hypothesis that all risk prices are jointly zero is strongly rejected. Finally, the null that the pricing errors are all zero can be rejected at the 1% level but not at the 5% level (p-value = 3.9%). The results look similar in the 1980-2012 sample, reported in the second column. In the third column, we add the corporate bond portfolios and the MAPE falls further to 63 bps, while the market prices of risk are similar to those in the second column.

In the next three columns of Table A.III we use YGR alongside the MKT and LVL factors in our asset pricing exercise. The YGR SDF generates a low pricing error in the full sample and in the post-1980 sample. It continues to do well once we add credit portfolios and re-estimate the SDF. The results are comparable to the CP SDF. Also, the market price of risk estimates are comparable to those of the CP SDF model. We strongly reject the null that all market price of risk estimates are zero. We cannot reject the null that all pricing errors are zero. The p-values are the highest of all of our models. We find similar pricing results for the linear combination of 1- through 5-year bond yields that best forecasts CFNAI 24-months ahead, and for the linear combination that best forecasts GDP growth 5 quarters ahead (unreported).

Table A.III: Alternative Yield Curve Factors

This table reports pricing errors on five book-to-market sorted quintile stock portfolios, the value-weighted market portfolio, five bond portfolios of maturities 1, 2, 5, 7, and 10 years, and four credit-sorted portfolios. They are expressed in percent per year (monthly numbers multiplied by 1200). We also report the mean absolute pricing error across all securities (MAPE) and the estimates of the prices of risk. The first three columns correspond to the YSP SDF, the middle three columns to the YGR SDF, while the last three columns refer to the YAP SDF model. YSP is the slope of the yield curve, measured as the difference between the 5-year bond yield and the one-year bond yield. YGR is the fitted value of a regression of macro-economic activity $CFNAI_{t+12}$ on the one- through five-year yields at time t. YAP is the linear combination of one- through five-year yields which best prices the 11 test assets in the full sample (minimizes the MAPE in column 4). The first, fourth, and seventh columns are for the full 1952-2012 sample, while the other columns are for the 1980-2012 sub-sample in which we observe corporate bond returns.

Panel A: Pricing Errors (% per year)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	YSP SDF			YGR SDF			YAP SDF		
10-yr	0.58	0.74	0.94	0.25	0.74	0.87	-0.19	0.00	0.42
7-yr	0.29	0.15	0.51	0.27	0.15	0.63	0.33	0.11	0.52
5-yr	-0.43	-0.53	-0.11	-0.18	-0.53	0.39	-0.06	0.09	0.42
2-yr	-1.09	-0.92	-0.52	-0.57	-0.92	-0.15	0.00	-0.26	-0.02
1-yr	-0.79	-0.52	-0.25	-0.74	-0.52	-0.06	-0.14	-0.02	0.12
Market	-0.89	-1.15	-1.17	-0.73	-1.15	-1.11	-0.61	-0.86	-0.90
BM1	-0.82	-1.07	-1.21	-0.11	-1.07	-0.64	0.02	0.03	-0.18
BM2	-0.49	0.39	0.34	-1.36	0.39	0.04	0.12	0.67	0.61
BM3	0.69	0.20	0.15	0.39	0.20	-0.21	0.48	0.06	0.06
BM4	0.74	0.37	0.52	1.08	0.37	0.79	-0.63	-0.72	-0.48
BM5	0.95	1.50	1.71	0.87	1.50	1.54	0.61	0.79	1.00
Credit1			-0.79			-0.78			-0.82
Credit2			-0.56			-0.71			-0.56
Credit3			-0.28			-0.63			-0.24
Credit4			0.38			0.06			0.20
MAPE	0.70	0.69	0.63	0.59	0.45	0.57	0.29	0.33	0.44
Panel B: Prices of Risk Estimates									
MKT	2.16	2.84	2.89	1.16	2.23	2.55	2.45	2.06	2.20
LVL	-4.67	-15.41	-22.54	-4.43	-13.28	-11.86	-19.99	-22.45	-19.81
YSP/YGR/YAP	100.13	66.25	53.20	112.01	79.83	50.76	71.37	53.37	46.87
Panel C: P-values of chi-squared Tests									
$\Lambda_0 = 0$	0.04%	0.53%	0.52%	1.80%	4.22%	2.19%	0.82%	2.41%	2.69%
Pr. err. = 0	3.86%	25.09%	13.50%	40.03%	77.07%	35.51%	24.52%	33.47%	4.65%

The last three columns of Table A.III show that the YAP SDF results in a very low MAPE of 29bp in the full sample. This is by construction. The risk price estimate of YAP (which has the same volatility of CP through a rescaling) is comparable to that of CP and not statistically different from it. Pricing errors continue to be low in the post-1980 sample, even though the linear combination is kept constant across samples. The results for the YAP and CP SDF models are similar because YAP has a high correlation of 74% with CP. Like CP it is a predictor of economic activity at somewhat higher lag lengths than YSP and YGR. I.e., it is an early warning indicator of economic activity.

B.5. Business Cycle versus Long-Run Risks

To disentangle the business-cycle frequency from the low-frequency component of the yield curve factor and to figure out which component is best at pricing the joint cross-section of stocks and bonds, we construct three pricing factors and compare their pricing ability. The first pricing factor is a linear combination of yields that predicts 1-year GDP growth best. We label this factor $GDP1$. For the second factor, we first find a linear combination of yields that predicts 5-year GDP growth best. We label this factor $GDP5$. These factors are virtually uncorrelated. If we regress $GDP1$ on $GDP5$, the full-sample R-squared is only 3.1%. We label the residual of this regression as $GDP1 - Ortho$, which is by constructional orthogonal to $GDP5$. The latter factor isolates business-cycle frequency dynamics by construction. We use these three factors as pricing factors for our cross-section, alongside the market and the level factors. Table A.IV reports the pricing errors for each of our 11 basic test assets as well as the mean absolute pricing error.

Table A.IV: Comparing pricing factors based on business-cycle and long-run growth risk.

	$GDP1$	$GDP1 - Ortho$	$GDP5$
10-yr	0.20	0.06	-0.33
7-yr	0.38	0.42	0.15
5-yr	-0.07	0.04	0.04
2-yr	-0.80	-0.68	0.18
1-yr	-0.82	-0.82	0.39
Market	-0.80	-0.70	-1.29
BM1	-0.28	-0.07	-2.27
BM2	-1.33	-1.36	-0.75
BM3	0.25	0.12	0.63
BM4	1.07	0.85	1.53
BM5	1.22	1.24	2.50
MAPE	0.66	0.58	0.91

Consistent with our main results, $GDP1$ does a good job explaining the cross-section of stock and bond returns. The MAPE is 66bp per year. Second, if we remove the long-run/low-frequency component by projecting $GDP1$ on $GDP5$, the pricing performance *further improves*. The MAPE falls from 66bp to 58bp. Third, consistent with this finding, $GDP5$ does not do as well in pricing the cross-section of returns, and the MAPE increases to 91bp.

Taken together, these results suggest that linear combinations of yields that predict near-term growth fare better in pricing the cross section of stock and bond returns than linear combinations of yields that predict long-term growth. We confirmed these results using an alternative yield curve variable which is the factor that best predicts CFNAI one-year ahead, orthogonalized to the factor that best predicts CFNAI 5-years out.

B.6. Bootstrap Exercise

One possibility we want to rule out is that the CP factor is spuriously related to the cross-section of stock and bond returns. That spurious relationship could arise because the test assets have a strong factor structure with roughly three dimensions (value-growth, market, and bond maturity) and we have three asset pricing factors to explain them (see Lewellen, Shanken, and Nagel, 2010). Furthermore, the CP factor is a generated regressor, which could affect the inference. To investigate the possibility of spurious factors and to deal with the generated nature of the CP regressor, we construct a set of bond yields that have the same persistence and covariance structure as in the data but that are otherwise *pure noise*. That is, their innovations are random. From those spurious bond yields, we estimate the CP factor, the yield spread YSP, and the level factor LVL. We combine CP or YSP with LVL and MKT factors to price the cross-section of test assets (stocks, Treasury bonds, and corporate bonds). We include corporate bonds since Lewellen, Shanken, and Nagel (2010) suggest to include as wide a cross-section as possible to add dimensions of risk. We repeat this exercise 5,000 times and count the number of times the mean absolute pricing error (MAPE) among the test assets is higher than the point estimate in the data. That is the p-value of our MAPE. Note that this procedure takes into account the generated nature of the CP factor.

Specifically, we first stack five bond yields of maturities one through five years in a vector, $\bar{y}_t$. The data are the standard Fama-Bliss bond yields. We estimate a first-order VAR for these yields at monthly frequency:

$$\bar{y}_{t+1} = \mu_y + \Gamma_y \bar{y}_t + \Sigma_y u_{t+1}. \tag{A.3}$$

Denote the VAR coefficient estimates by $\hat{\mu}_y$, $\hat{\Gamma}_y$, and $\hat{\Sigma}_y$. The $T \times 5$ panel of yield innovations is u. Next, in each bootstrap iteration we draw with replacement a $T \times 5$ panel of Gaussian innovations for yields. We impose that these innovations have a covariance matrix equal to $\hat{\Sigma}_y\hat{\Sigma}_y'$. The sample length is the same as in the data. Using $\hat{\mu}_y$ and $\hat{\Gamma}_y$, the simulated yield innovations, and the initial yield vector from the data, we rebuild a panel of bond yields. We also draw a panel of $T \times 15$ test asset returns with replacement, preserving the cross-correlation structure between the test asset returns. Thus, for each bootstrap iteration we obtain a panel of re-sampled returns and bond yields, where the bond yields are entirely random.

We then run the exact same estimation code as we do for the real data and record the MAPE. This includes re-estimating the CP factor from the simulated yields or constructing the yield spread YSP. It includes estimating the LVL factor as the first principal component of the generated bond yields. It also includes re-estimating the first-order VAR for the three asset pricing factors (CP or YSP, LVL, and MKT) to obtain the VAR innovations which we need to perform the cross-sectional asset pricing estimation. And it includes forming unexpected test asset returns as residuals from regressions of returns on the lagged conditioning variable (CP or YSP). All estimation error introduced by these estimation steps will be reflected in the p-values.

We repeat this exercise 5,000 times. We then compute the fraction of times the MAPE we find in our paper is larger than the MAPE we find using random factors. This is the p-value we report in the main text. If our model fares better than when using random yield-based pricing factors, we expect a low p-value. Note that because we draw the market return jointly with the other returns, the reference point for the MAPE is the CAPM pricing kernel. We find a p-value of 3.5% for the CP model and 11.5% for the YSP model. Even though the pricing model that includes the CP factor instead of the yield spread requires an additional estimation step, the significance of the reduction in pricing errors is higher. These findings clarify that our pricing results are not a consequence of random factors, despite the strong factor structure inherent in a cross-section that includes equity, Treasury bond, and corporate bond portfolios.

B.7. Other Test Assets

We also study book-to-market decile instead of quintile portfolios, alongside the same bond portfolios and the aggregate stock market portfolio. The value spread between the tenth and first book-to-market portfolios is 4.94% per annum, 81 bps higher than between the extreme quintile portfolios. Our CP SDF model's residual MAPE is a mere 50 bps and generates a value premium of 4.67%. The YSP SDF model performs better on this set of 16 test assets with a MAPE of 66 bps and a predicted value premium of 4.16%. The market price of risk estimates are very similar to those obtained with the quintile portfolios. Again, the null hypothesis that all market prices of risk are jointly zero is strongly rejected, while the null that all pricing errors are jointly zero cannot be rejected; the p-value is 19% for the CP SDF and 18% for the YSP SDF model. The Fama-French model is in between these with a MAPE of 59 bps, but with a lower p-value allowing us to statistically reject the FF model. Detailed results are available upon request.

Table A.V shows three exercises where we replace the book-to-market sorted equity portfolios by other equity portfolios. In the first four columns we use ten market capitalization-sorted portfolios alongside the bond portfolios and the market. The first column shows the risk premia to be explained (risk neutral SDF). Small firms (S1) have 3.6% higher risk premia than large stocks (S10). Our CP SDF model in the second column manages to bring the overall mean absolute pricing error down from 6.27% per year to 0.34% per year, while our YSP SDF model has an even lower MAPE of 31bp. The market prices of risk are not statistically different from those estimated on book-to-market portfolios instead of size portfolios. We fail to reject the null that all pricing errors are zero at the 1% level but not at the 5% level. These MAPEs are somewhat lower than the 57bp in the Fama-French model in the fourth column. The Fama-French model does better eliminating the spread between small and large stocks, whereas our model does better pricing the bond portfolios.

The next three columns use earnings-price-sorted decile stock portfolios. The highest earnings-price portfolio has an average risk premium that is 6.3% higher per year than the lowest earnings-price portfolio. Our CP SDF model reduces this spread in risk premia to 1.8% per year, while continuing to price the bonds reasonably well. The MAPE is 111 basis points per year compared to 142 for the YSP SDF, and 76bp in the Fama-French model.

The last three columns use the five-by-five market capitalization and book-to-market double sorted portfolios. Our CP SDF model manages to bring the overall mean absolute pricing error down from 7.7% per year to 1.3% per year while the YSP SDF model has a 1.2% MAPE. This is again comparable to the three-factor Fama-French model's MAPE of 1.2%.

The market price of risk estimates Λ_0 in Panel B of Table A.V are comparable to those we found for the book-to-market portfolios in Table 1. Panel C shows that we reject the null hypothesis that all market prices of risk are zero for all three sets of test assets. We fail to reject the null hypothesis that all pricing errors are zero on the size and earnings-price portfolios. We conclude that these results are in line with our benchmark results and that they further strengthen the usefulness of our empirical three-factor model.

B.8. Individual Firm Returns: Double Sorts

We double sort stocks into five quintiles based on their CP exposure and then, within CP quintile, on their book-to-market (BM) ratio. This results in a 5×5 sort or 25 portfolios that differ by their CP exposure and B/M ratio. Table A.VI shows that we find a positive spread between high and low CP-exposure portfolios for each BM group, with spreads ranging from 0.5% to 4.6% per year. We also find that the spread between high and low BM portfolios is positive in each CP group. This could imply that CP exposures and BM are related, yet not the same. Or it could reflect estimation error in CP exposures that prevents CP exposure from fully subsuming BM exposure. Turning to the pricing, we find that the CAPM model cannot explain the heterogeneity in average returns on the 25 portfolios along either dimension. The MAPE of the CAPM is 171 bps per year. In contrast, our three-factor model eliminates a substantial fraction of the spread along *both* CP and BM dimensions. The MAPE reduces to 100 bps. Ex-post CP exposures are higher for the portfolios with higher ex-ante CP exposures as well as for portfolios with higher BM ratios. In further support for our model, we find comparable market price of risk estimates to the benchmark ones, but now obtained from this double-sorted cross-section of equity portfolios. For the market price of CP risk we estimate 71, quite similar to the 74 estimate that obtains when we estimate our model on the 11 test assets on the post-1963 sample. For LVL risk we estimate -24 (-20 in benchmark) and for MKT we have 0.8 (compared to 1.3). Taken together, these results suggest that there are separate spreads along the dimensions of ex-ante CP exposure and BM ratio. However, both spreads are to a large extent accounted for by our model, and with risk prices that are similar to those we estimated using other cross-sections of assets.

Table A.V: Other Stock Portfolios - Pricing Errors

This table reports robustness with respect to different stock market portfolios, listed in the first row. Panel A of this table reports pricing errors (in % per year) on various stock portfolios, the value-weighted market portfolio, and five bond portfolios of maturities 1, 2, 5, 7, and 10 years. Each column corresponds to a different stochastic discount factor (SDF) model. The first column contains the risk-neutral SDF. The second column presents our CP SDF model with three priced factors while the third column presents our YSP SDF model. The fourth column refers to the three factor model of Fama and French (FF). The last row of Panel A reports the mean absolute pricing error across all securities (MAPE). Panel B reports the estimates of the prices of risk. The data are monthly from June 1952 through December 2012.

Panel A: Pricing Errors (in % per year)														
	Size Portfolios					EP Portfolios					Size and Value Portfolios			
	RN SDF	CP SDF	YSP SDF	FF		RN SDF	CP SDF	YSP SDF	FF		RN SDF	CP SDF	YSP SDF	FF
10-yr	1.76	0.21	0.37	1.15		1.76	0.71	0.83	1.17		1.76	0.37	0.59	1.51
7-yr	2.08	0.48	0.34	1.90		2.08	0.55	0.12	1.73		2.08	0.26	-0.46	2.03
5-yr	1.72	-0.09	-0.19	1.38		1.72	-0.68	-0.90	1.39		1.72	-0.91	-1.70	1.61
2-yr	1.22	-0.50	-0.62	0.83		1.22	-1.85	-1.92	0.95		1.22	-1.91	-2.84	1.06
1-yr	0.97	-0.30	-0.39	0.68		0.97	-1.48	-1.49	0.79		0.97	-1.48	-2.20	0.84
Market	6.58	-0.56	-0.61	-0.22		6.58	-1.25	-1.46	-0.43		6.58	0.30	0.49	0.10
ME1	9.54	0.98	0.68	-0.20	EP1	5.81	-0.06	-1.46	1.31	S1B1	3.51	-4.16	-5.91	-5.17
ME2	9.21	-0.13	-0.28	0.06	EP2	5.23	-1.58	-2.62	-0.88	S1B2	9.57	-0.72	-0.21	0.42
ME3	9.80	0.69	0.52	0.30	EP3	6.43	-0.81	-1.28	-0.18	S1B3	9.86	-0.83	-0.38	0.53
ME4	9.06	0.14	0.01	0.19	EP4	6.44	-1.49	-0.54	-0.75	S1B4	12.00	2.91	1.92	2.15
ME5	9.37	0.05	0.20	0.45	EP5	7.04	-0.93	-1.08	-0.89	S1B5	13.61	2.90	2.20	1.90
ME6	8.75	-0.08	-0.01	0.07	EP6	8.66	0.64	0.87	-0.15	S2B1	5.65	-1.94	-2.55	-1.72
ME7	8.65	-0.29	0.06	0.23	EP7	9.27	0.43	1.23	0.38	S2B2	8.96	-0.26	-0.59	0.18
ME8	8.17	-0.58	-0.33	-0.51	EP8	9.99	2.45	2.70	0.28	S2B3	11.04	1.02	1.38	1.63
ME9	7.48	-0.12	-0.05	-0.81	EP9	10.85	1.03	1.74	0.19	S2B4	11.17	1.11	0.58	0.88
ME10	5.95	-0.25	-0.34	0.15	EP10	12.09	1.73	2.52	0.62	S2B5	12.37	2.33	0.67	-0.06
										S3B1	6.87	-1.62	-2.10	0.56
										S3B2	9.40	0.13	0.33	0.99
										S3B3	9.63	-0.20	0.25	0.39
										S3B4	10.84	0.15	0.25	0.75
										S3B5	12.09	1.65	2.31	0.50
										S4B1	7.40	0.23	-0.17	1.87
										S4B2	7.48	-1.04	-0.04	-0.71
										S4B3	9.42	0.30	0.54	0.14
										S4B4	9.96	-1.59	-0.27	0.22
										S4B5	9.99	-1.56	-0.09	-1.71
										S5B1	6.07	2.31	2.16	1.99
										S5B2	6.62	1.99	1.28	0.24
										S5B3	7.03	1.49	1.98	-0.16
										S5B4	6.99	-1.21	0.70	-2.05
										S5B5	7.94	-0.86	-0.34	-2.66
MAPE	6.27	0.34	0.31	0.57		6.01	1.11	1.42	0.76		7.74	1.28	1.21	1.18
Panel B: Prices of Risk Estimates														
MKT		2.39	2.32	6.52			1.87	1.91	4.79			1.18	0.54	3.79
LVL/SMB		-16.50	-6.01	0.59			-26.11	-3.05	-1.26			-27.97	-5.02	1.77
CP/YSP/HML		72.17	70.78	21.64			168.19	149.35	8.79			163.84	193.73	7.63
Panel C: P-values of chi-squared Tests														
$\Lambda_0 = 0$		0.89%	0.34%	1.06%			0.85%	0.06%	0.00%			0.39%	0.22%	0.00%
Pr. err. = 0		3.61%	1.59%	0.87%			13.18%	2.17%	0.02%			0.83%	0.32%	0.00%

Table A.VI: Individual Firm Returns: Double Sorts

This table reports the results of sorting individual firms into 25 portfolios based on their exposure to CP shocks and B/M ratio. We use 60-month rolling window estimates of CP betas, where we require at least 12 months of data for a stock to be included in one of the portfolios. We first sort stocks on CP betas into five portfolios, and then sort each of these groups into 5 portfolios based on their B/M ratio. The table reports the average excess return per portfolio, the CAPM alphas, the alphas for the KLN model, the CP exposures of the five portfolios, the risk prices, and MAPE for the different models. The data are monthly from July 1963 through December 2010.

Average excess returns	Low B/M				High B/M	H-L B/M				
Low CP exposure	2.1%	3.2%	7.7%	7.0%	8.0%	5.9%				
	4.6%	5.1%	4.7%	7.3%	7.4%	2.8%				
	5.2%	5.1%	6.0%	6.8%	8.8%	3.6%				
	5.4%	5.4%	7.1%	10.9%	8.7%	3.3%				
High CP exposure	4.7%	7.8%	8.2%	9.2%	10.1%	5.4%				
High-low CP exposure	2.6%	4.6%	0.5%	2.2%	2.1%					
							Risk prices			
CAPM alphas	Low B/M				High B/M	H-L B/M	CP	LVL	MKT	MAPE
Low CP exposure	-5.8%	-3.8%	0.9%	0.1%	0.5%	6.3%			2.50	171bp
	-1.8%	-1.1%	-0.8%	1.5%	0.7%	2.5%				
	-1.0%	-0.9%	0.8%	1.2%	2.7%	3.7%				
	-1.3%	-0.9%	0.8%	4.8%	2.2%	3.5%				
High CP exposure	-3.1%	0.6%	1.2%	2.0%	2.5%	5.6%				
High-low CP exposure	2.7%	4.5%	0.3%	1.9%	2.0%					
							Risk prices			
KLN alphas	Low B/M				High B/M	H-L B/M	CP	LVL	MKT	MAPE
Low CP exposure	-1.3%	-2.3%	0.8%	-0.8%	-1.0%	0.3%	71.34	-24.44	0.78	100bp
	1.0%	0.1%	-1.6%	-0.9%	-0.1%	-1.1%				
	1.2%	0.0%	-1.2%	-1.0%	1.8%	0.6%				
	-0.6%	-0.4%	0.6%	2.5%	1.7%	2.3%				
High CP exposure	-0.6%	2.2%	-0.8%	0.5%	0.2%	0.8%				
High-low CP exposure	0.7%	4.5%	-1.6%	1.3%	1.2%					
CP covariances ($\times 10^5$)	Low B/M				High B/M	H-L B/M				
Low CP exposure	-0.27	2.34	3.61	5.37	6.91	7.18				
	-0.02	1.55	3.41	5.36	5.07	5.09				
	-0.05	1.76	4.43	4.89	4.60	4.64				
	2.12	2.18	3.46	5.60	4.54	2.42				
High CP exposure	2.02	2.51	5.60	5.86	7.05	5.03				
High-low CP exposure	2.29	0.16	1.99	0.49	0.14					

C. How Pricing Stocks and Bonds Jointly Can Go Wrong

Consider two factors F_t^i, $i = 1, 2$, with innovations η_{t+1}^i. We normalize $\sigma\left(\eta_{t+1}^i\right) = 1$. Let $cov\left(\eta_{t+1}^1, \eta_{t+1}^2\right) = \rho = corr\left(\eta_{t+1}^1, \eta_{t+1}^2\right)$. We also have two cross-sections of test assets with excess, geometric returns r_{t+1}^{ki}, $i = 1, 2$ and $k = 1, ..., K_i$, with innovations ε_{t+1}^{ki}. We assume that these returns include the Jensen's correction term. Suppose that both cross-sections exhibit a one-factor pricing structure:

$$E\left(r_{t+1}^{ki}\right) = cov\left(\varepsilon_{t+1}^{ki}, \eta_{t+1}^i\right)\lambda_i,\ i = 1, 2.$$

The first factor perfectly prices the first set of test assets, whereas the second factor prices the second set of test assets. We show below that this does *not* imply that there exists a single SDF that prices both sets of assets.

Consider the following model of unexpected returns for both sets of test assets:

$$\begin{aligned}
\varepsilon_{t+1}^{k1} &= E\left(r_{t+1}^{k1}\right)\eta_{t+1}^1, \\
\varepsilon_{t+1}^{k2} &= E\left(r_{t+1}^{k2}\right)\eta_{t+1}^2 + \alpha_{2k}\eta_{t+1}^3,
\end{aligned}$$

with $cov\left(\eta_{t+1}^2, \eta_{t+1}^3\right) = 0$. Unexpected returns on the first set of test assets are completely governed by innovations to the first factor, whereas unexpected returns on the second set of test assets contain a component $\alpha_{2k}\eta_{t+1}^3$ that is orthogonal to the component governed by innovations to the second factor. These η^3 shocks are not priced (by assumption). We assume that they are correlated with the η^1 shocks: $cov\left(\eta_{t+1}^1, \eta_{t+1}^3\right) \neq 0$.

This structure implies:

$$cov\left(\varepsilon_{t+1}^{ki}, \eta_{t+1}^i\right) = E\left(r_{t+1}^{ki}\right) var\left(\eta_{t+1}^i\right) = E\left(r_{t+1}^{ki}\right),$$

and hence $\lambda_i = 1$, $i = 1, 2$. Then we have:

$$\begin{aligned}
cov\left(\varepsilon_{t+1}^{k1}, \eta_{t+1}^1\right) &= E\left(r_{t+1}^{k1}\right), & cov\left(\varepsilon_{t+1}^{k1}, \eta_{t+1}^2\right) &= E\left(r_{t+1}^{k1}\right)\rho, \\
cov\left(\varepsilon_{t+1}^{k2}, \eta_{t+1}^1\right) &= \left(r_{t+1}^{k2}\right)\rho + \alpha_{2k} cov\left(\eta_{t+1}^1, \eta_{t+1}^3\right), & cov\left(\varepsilon_{t+1}^{k2}, \eta_{t+1}^2\right) &= E\left(r_{t+1}^{k2}\right).
\end{aligned}$$

The main point is that, if α_{2k} is not proportional to $E\left(r_{t+1}^{k2}\right)$, then there exist no Λ_1 and Λ_2 such that:

$$E\left(r_{t+1}^{ki}\right) = cov\left(\varepsilon_{t+1}^{ki}, \eta_{t+1}^1\right)\Lambda_1 + cov\left(\varepsilon_{t+1}^{ki}, \eta_{t+1}^2\right)\Lambda_2.$$

On the other hand, if there is proportionality and $\alpha_{2k} = \alpha E\left(r_{t+1}^{k2}\right)$, then we have:

$$cov\left(\varepsilon_{t+1}^{k2}, \eta_{t+1}^1\right) = E\left(r_{t+1}^{k2}\right)\left(\rho + \alpha cov\left(\eta_{t+1}^1, \eta_{t+1}^3\right)\right) = E\left(r_{t+1}^{k2}\right)\xi,$$

and Λ_1 and Λ_2 are given by:

$$\Lambda_1 = \frac{1-\rho}{1-\xi\rho}, \text{and } \Lambda_2 = \frac{1-\xi}{1-\xi\rho}.$$

This setup is satisfied approximately in our model, where the first set of test assets are the book-to-market portfolios, η^1 are CP innovations, the second set of test assets are the bond portfolios, and η^2 are LVL innovations. Unexpected bond returns contain a component η^3 that is uncorrelated with LVL innovations, but that is correlated with CP innovations. Unexpected book-to-market portfolio returns, in contrast, are largely uncorrelated with LVL innovations. The result above illustrates that consistent risk pricing is possible because unexpected bond returns' exposure to CP shocks has a proportionality structure. This can also be seen in the top panel of Figure 5.

D. Structural Model with Business Cycle Risk

This appendix sets up and calibrates a structural asset pricing model that connects our empirical findings in a transparent way. The model formalizes the relationships between the returns on value and growth stocks, the CP factor, and the state of the macro-economy. It does so in a unified pricing framework that can quantitatively account for the observed risk premia on stock and bond portfolios, while being consistent with the observed dynamics of dividend growth rates, inflation, and basic properties of the term structure of interest rates. Its role is largely pedagogical: to clarify the minimal structure necessary to account for the observed moments. We start by describing the setup and provide the derivations of the asset pricing expressions. We also discuss the parameters used in the numerical example, and how they were chosen.

D.1. Setup

The model has one key state variable, s, which measures macroeconomic activity. One interpretation of s is as a leading business cycle indicator. This state variable follows an autoregressive process, with modest persistence, and its innovations ε^s_{t+1} are the first priced source of risk.

$$s_{t+1} = \rho_s s_t + \sigma_s \varepsilon^s_{t+1}.$$

Higher values of s denote higher economic activity. The model permits an interpretation of s as a signal about *future* economic activity. Since this variable moves at business cycle frequency, the persistence ρ_s is moderate.

Real dividend growth on asset $i = \{G, V, M\}$ (Value, Growth, and the Market) is given by:

$$\Delta d^i_{t+1} = \gamma_{0i} + \gamma_{1i} s_t + \sigma_{di} \varepsilon^d_{t+1} + \sigma_i \varepsilon^i_{t+1}. \tag{A.4}$$

If $\gamma_{1i} > 0$, dividend growth is pro-cyclical. The shock ε^d_{t+1} is an aggregate dividend shock, while ε^i_{t+1} is an (non-priced) idiosyncratic shock; the market portfolio has no idiosyncratic risk; $\sigma_M = 0$. The key parameter configuration is $\gamma_{1V} > \gamma_{1G}$ so that value stocks are more exposed to cyclical risk than growth stocks. As is the data (Section 2.2.1), a low value for s is associated with lower future dividend growth on V minus G. Below, we will calibrate γ_{1V} and γ_{1G} to capture the decline in dividend growth value minus growth over the course of recessions.

Inflation is the sum of a constant, a mean-zero autoregressive process which captures expected inflation, and an unexpected inflation term:

$$\begin{aligned}
\pi_{t+1} &= \bar{\pi} + x_t + \sigma_\pi \varepsilon^\pi_{t+1}, \\
x_{t+1} &= \rho_x x_t + \sigma_x \varepsilon^x_{t+1}.
\end{aligned}$$

All shocks are cross-sectionally and serially independent and standard normally distributed. It would be straightforward to add a correlation between inflation shocks and shocks to the business cycle variable. This inflation process is common in the literature (e.g., Wachter, 2006; Bansal and Shaliastovich, 2010).

To simplify our analysis, we assume that market participants' preferences are summarized by a real stochastic discount factor (SDF), whose log evolves according to the process:

$$-m_{t+1} = y + \frac{1}{2}\Lambda_t' \Lambda_t + \Lambda_t' \varepsilon_{t+1}.$$

where the vector $\varepsilon_{t+1} \equiv \left(\varepsilon^d_{t+1}, \varepsilon^x_{t+1}, \varepsilon^s_{t+1}\right)'$ and y is the real interest rate. The risk price dynamics are affine in the state of the economy s_t:

$$\Lambda_t = \Lambda_0 + \Lambda_1 s_t$$

As in the reduced form model in the main text, the structural model features three priced sources of risk: aggregate dividend growth risk, which carries a positive price of risk ($\Lambda_0(1) > 0$), inflation risk ($\Lambda_0(2) < 0$), and cyclical risk ($\Lambda_0(3) > 0$). Choosing $\Lambda_1(2) < 0$ makes the price of inflation risk counter-cyclical. As we show below, this makes bond risk premia increase pro-cyclical. We also set $\Lambda_1(1) > 0$ resulting in a pro-cyclical price of aggregate dividend risk. The log nominal SDF is given by $m^\$_{t+1} = m_{t+1} - \pi_{t+1}$. For similar approaches to the SDF, see Bekaert, Engstrom, and

Xing (2009), Bekaert, Engstrom, and Grenadier (2010), Lettau and Wachter (2009), Campbell, Sunderam, and Viceira (2012), and David and Veronesi (2009).

D.2. Asset Prices

We now study the equilibrium bond and stock prices in this model. The model generates an affine nominal term structure of interest rates. It also generates a one-factor model for the nominal bond risk premium: All variation in bond risk premia comes from cyclical variation in the economy, s_t. Thus, the CP factor which measures the bond risk premium in the model is perfectly positively correlated with s_t, the (leading) indicator of macroeconomic activity.

D.2.1. Bond Prices and Risk Premia

It follows immediately from the specification of the real SDF that the real term structure of interest rates is flat at y. Nominal bond prices are exponentially affine in the state of the economy and in expected inflation:

$$P_t^{\$}(n) = \exp\left(A_n^{\$} + B_n^{\$} s_t + C_n^{\$} x_t\right),$$

with coefficients that follow recursions described in the proof below. As usual, nominal bond yields are $y_t^{\$}(n) = -\log(P_t^{\$}(n))/n$.

Proof. The nominal SDF is given by:

$$\begin{aligned} m_{t+1}^{\$} &= m_{t+1} - \pi_{t+1} \\ &= -y - \bar{\pi} - x_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\varepsilon_{t+1} - \sigma_\pi \varepsilon_{t+1}^{\pi} \end{aligned}$$

The price of an n-period bond is given by:

$$P_t^n = \exp\left(A_n^{\$} + B_n^{\$} s_t + C_n^{\$} x_t\right).$$

The recursion of nominal bond prices is given by:

$$\begin{aligned} P_t^n &= E_t\left(P_{t+1}^{n-1} M_{t+1}^{\$}\right) \\ &= E_t\left(\exp\left(A_{n-1}^{\$} + B_{n-1}^{\$} s_{t+1} + C_{n-1}^{\$} x_{t+1} - y - \bar{\pi} - x_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\varepsilon_{t+1} - \sigma_\pi \varepsilon_{t+1}^{\pi}\right)\right) \\ &= \exp\left(A_{n-1}^{\$} - y - \bar{\pi} - x_t - \frac{1}{2}\Lambda_t'\Lambda_t^{+} B_{n-1}^{\$}\rho_s s_t + C_{n-1}^{\$}\rho_x x_t\right) \times \\ &\quad E_t\left(\exp\left(B_{n-1}^{\$}\sigma_s \varepsilon_{t+1}^{s} + C_{n-1}^{\$}\sigma_x \varepsilon_{t+1}^{x} - \Lambda_t'\varepsilon_{t+1} - \sigma_\pi \varepsilon^{\pi} t + 1\right)\right) \\ &= \exp\left(A_{n-1}^{\$} - y - \bar{\pi} - x_t + B_{n-1}^{\$}\rho_s s_t + C_{n-1}^{\$}\rho_x x_t\right) \times \\ &\quad \exp\left(\frac{1}{2}[B_{n-1}^{\$}]^2\sigma_s^2 + \frac{1}{2}[C_{n-1}^{\$}]^2\sigma_x^2 - B_{n-1}^{\$}\sigma_s\Lambda_t(3) - C_{n-1}^{\$}\sigma_x\Lambda_t(2) + \frac{1}{2}\sigma_\pi^2\right), \end{aligned}$$

which implies:

$$\begin{aligned} A_n^{\$} &= A_{n-1}^{\$} - y - \bar{\pi} + \frac{1}{2}[B_{n-1}^{\$}\sigma_s]^2 + \frac{1}{2}[C_{n-1}^{\$}\sigma_x]^2 + \frac{1}{2}\sigma_\pi^2 - B_{n-1}^{\$}\sigma_s\Lambda_0(3) - C_{n-1}^{\$}\sigma_x\Lambda_0(2), \\ B_n^{\$} &= B_{n-1}^{\$}\rho_s - C_{n-1}^{\$}\sigma_x\Lambda_1(2), \\ C_n^{\$} &= -1 + C_{n-1}^{\$}\rho_x. \end{aligned}$$

The starting values for the recursion are $A_0^\$ = 0$, $B_0^\$ = 0$, and $C_0^\$ = 0$. □

The expression for $C_n^\$$ can be written more compactly as:

$$C_n^\$ = -\frac{1-\rho_x^n}{1-\rho_x}\rho_x < 0,$$

implying that bond prices drop -and nominal interest rates increase- when inflation increases: $C_n^\$ < 0$. Consistent with the data, we assume that $\Lambda_1(2) < 0$. It follows that $B_n^\$ < 0$, implying that nominal bond prices fall -and nominal interest rates rise- with the state of the economy (s_t). Both signs seem consistent with intuition.

The nominal bond risk premium, the expected excess log return on buying an n-period nominal bond and selling it one period later (as a $n-1$-period bond), is given by:

$$\begin{aligned} E_t\left[rx_{t+1}^\$(n)\right] &= -cov_t\left(m_{t+1}^\$, B_{n-1}^\$ s_{t+1} + C_{n-1}^\$ \pi_{t+1}\right) \\ &= cov_t\left(\Lambda_t'\varepsilon_{t+1}, B_{n-1}^\$ s_{t+1} + C_{n-1}^\$ x_{t+1}\right) \\ &= \Lambda_t(2)C_{n-1}^\$\sigma_x + \Lambda_t(3)B_{n-1}^\$\sigma_s \\ &= \underbrace{\Lambda_0(2)C_{n-1}^\$\sigma_x + \Lambda_0(3)B_{n-1}^\$\sigma_s}_{\text{Constant component bond risk premium}} + \underbrace{\Lambda_1(2)C_{n-1}^\$\sigma_x s_t}_{\text{Time-varying component bond risk premium}}, \end{aligned}$$

In this model, all of the variation in bond risk premia comes from cyclical variation in the economy, s_t. This lends the interpretation of CP factor to s_t which is consistent with our empirical evidence. Innovations to the CP factor are innovations to s (ε^s). Because $C_{n-1}^\$ < 0$, $\Lambda_1(2) < 0$ generates lower bond risk premia when economic activity is low ($s_t < 0$).

The constant component of the bond risk premium partly reflects compensation for cyclical risk and partly exposure to expected inflation risk. Exposure to the cyclical shock contributes negatively to excess bond returns: A positive ε^s shock lowers bond prices and returns, and more so for long than for short bonds. Exposure to expected inflation shocks contributes positively to excess bond returns: A positive ε^x shock lowers bond prices and returns but the price of expected inflation risk is negative. Since common variation in bond yields is predominantly driven by the inflation shock in the model, the latter acts like (and provides a structural interpretation for) a shock to the level of the term structure (LVL). Long bonds are more sensitive to level shocks, the traditional duration effect.

D.2.2. Stock Prices, Equity Risk Premium, Value Premium

The log price-dividend (pd) ratio on stock (portfolio) i is affine in s_t:

$$pd_t^i = A_i + B_i s_t,$$

where

$$B_i = \frac{\gamma_{1i} - \Lambda_1(1)\sigma_{di}}{1-\kappa_{1i}\rho_s},$$

and the expression for A_i is given in the proof below.

Proof. The return definition implies:

$$\begin{aligned} r_{t+1} &= \ln\left(\exp\left(pd_{t+1}\right)+1\right) + \Delta d_{t+1} - pd_t \\ &\simeq \ln\left(\exp\left(\overline{pd}\right)+1\right) + \frac{\exp\left(\overline{pd}\right)}{\exp\left(\overline{pd}\right)+1}\left(pd_{t+1}-\overline{pd}\right) + \Delta d_{t+1} - pd_t \\ &= \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t, \end{aligned}$$

where:

$$\kappa_0 = \ln\left(\exp\left(\overline{pd}\right)+1\right) - \kappa_1\overline{pd},$$
$$\kappa_1 = \frac{\exp\left(\overline{pd}\right)}{\exp\left(\overline{pd}\right)+1}.$$

We conjecture that the log price-dividend ratio is of the form:

$$pd_t = A + Bs_t,$$

The price-dividend ratio coefficients are obtained by solving the Euler equation:

$$E_t\left(M^{\$}_{t+1}R^{\$}_{t+1}\right) = 1.$$

We suppress the dependence on i in the following derivation:

$$\begin{aligned}
1 &= E_t\left(\exp\left(m_{t+1} - \pi_{t+1} + \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t + \pi_{t+1}\right)\right) \\
0 &= E_t\left(m_{t+1}\right) + \frac{1}{2}V_t\left(m_{t+1}\right) + E_t\left(\kappa_0 + \Delta d_{t+1} + \kappa_1 pd_{t+1} - pd_t\right) \\
&\quad + \frac{1}{2}V_t\left(\Delta d_{t+1} + \kappa_1 pd_{t+1}\right) + Cov_t\left(-\Lambda_t'\varepsilon_{t+1}, \Delta d_{t+1} + \kappa_1 pd_{t+1}\right) \\
&= -y + \kappa_0 + \gamma_0 + \gamma_1 s_t + \left(\kappa_1 - 1\right)A + \left(\kappa_1\rho_s - 1\right)Bs_t \\
&\quad + \frac{1}{2}\sigma_d^2 + \frac{1}{2}\sigma^2 + \frac{1}{2}\kappa_1^2B^2\sigma_s^2 - \Lambda_t(1)\sigma_d - \Lambda_t(3)\kappa_1 B\sigma_s.
\end{aligned}$$

This results in the system:

$$\begin{aligned}
0 &= -y + \kappa_0 + \gamma_0 + \left(\kappa_1 - 1\right)A + \frac{1}{2}\sigma_d^2 + \frac{1}{2}\sigma^2 + \frac{1}{2}\kappa_1^2B^2\sigma_s^2 - \Lambda_0(1)\sigma_d - \Lambda_0(3)\kappa_1 B\sigma_s, \\
0 &= \left(\kappa_1\rho_s - 1\right)B - \Lambda_1(1)\sigma_d + \gamma_1,
\end{aligned}$$

Rearranging terms, we get the following expressions for the pd ratio coefficients, where we make the dependence on i explicit:

$$\begin{aligned}
A_i &= \frac{\frac{1}{2}\sigma_{di}^2 + \frac{1}{2}\sigma_i^2 + \frac{1}{2}\kappa_{1i}^2B_i^2\sigma_s^2 - \Lambda_0(1)\sigma_{di} - \Lambda_0(3)\kappa_{1i}B_i\sigma_s - y + \kappa_{0i} + \gamma_{0i}}{1-\kappa_{1i}}, \\
B_i &= \frac{\gamma_{1i} - \Lambda_1(1)\sigma_{di}}{1-\kappa_{1i}\rho_s}.
\end{aligned}$$

□

We note that B_i can be positive or negative depending on the importance of dividend growth predictability (γ_{1i}) and fluctuations in risk premia ($\Lambda_1(1)\sigma_{di}$). Stock i's price-dividend ratios is pro-cyclical ($B_i > 0$) when dividend growth is more pro-cyclical than the risk premium for the aggregate dividend risk of asset i: $\gamma_{1i} > \sigma_{di}\Lambda_1(1)$.

The equity risk premium on portfolio i can be computed to be:

$$\begin{aligned}
E_t\left[rx^i_{t+1}\right] &= cov_t\left(-m^{\$}_{t+1}, r^i_{t+1} + \pi_{t+1}\right) \\
&= cov\left(\Lambda_t'\varepsilon_{t+1}, \kappa_{1i}B_i\sigma_s\varepsilon^s_{t+1} + \sigma_{di}\varepsilon^d_{t+1}\right) \\
&= \underbrace{\Lambda_0(1)\sigma_{di} + \Lambda_0(3)\kappa_{1i}B_i\sigma_s}_{\text{Constant component equity risk premium}} + \underbrace{\Lambda_1(1)\sigma_{di}s_t}_{\text{Time-varying component equity risk premium}}.
\end{aligned}$$

The equity risk premium provides compensation for aggregate dividend growth risk (first term, ε^d) and for cyclical risk (second term, ε^s). Like bond risk premia, equity risk premia vary over time with the state of the economy s_t (third term). The model generates both an equity risk premium and a value premium. The reason for the value premium can be traced back to the fact that value stocks' dividends are more sensitive to cyclical shocks than those of growth stocks. As we showed above, the data suggest that value stocks' dividends fall more in recessions than those of growth stocks ($\gamma_{1V} > \gamma_{1G}$). With $\sigma_{dV} \approx \sigma_{dG}$, this implies that $B_V > B_G$. Because the price of cyclical risk $\Lambda_0(3)$ is naturally positive, the second term delivers the value premium. Put differently, in the model, as in the data, returns on value stocks are more exposed to bond risk premium shocks than returns on growth stocks.

D.2.3. Link with Reduced-form Model

To make the link with the reduced-form model of Section 3 clear, we study the link between the structural shocks and the reduced form shocks. In the model, shocks to the market return (MKT) are given a linear combination of ε^d and ε^s shocks:

$$\varepsilon^{MKT}_{t+1} \equiv r^M_{t+1} - E_t[r^M_{t+1}] = \sigma_{dM}\varepsilon^d_{t+1} + \kappa_{1M} B_M \sigma_s \varepsilon^s_{t+1}$$

We construct the CP factor in the same way as in the data, from yields on 1- through 5-year yields and average excess bond returns. Since the model has a two-factor structure for bond yields and forward rates, we use only the two- and the five-year forward rates as independent variables in the CP regression of average excess returns on forward rates. The model's CP factor is perfectly correlated with the process s, and has a innovations that differs by a factor σ^{CP}: $\varepsilon^{CP}_{t+1} = \varepsilon^s_{t+1}\sigma^{CP}$. Finally, since expected inflation drives most of the variation in bond yields in the model, LVL shocks in the model are proportional to expected inflation shocks: $\varepsilon^{LVL}_{t+1} = \varepsilon^x_{t+1}\sigma^L$. Denote $\tilde{\varepsilon} = [\varepsilon^{MKT}, \varepsilon^{LVL}, \varepsilon^{CP}]'$. Associated with $\tilde{\varepsilon}$, we can define market prices of risk $\tilde{\Lambda}$, such that SDF innovations remain unaltered: $\Lambda'_t\varepsilon_{t+1} = \tilde{\Lambda}'_t\tilde{\varepsilon}_{t+1}$. It is easy to verify that $\tilde{\Lambda}_0(1) = \Lambda_0(1)/\sigma_{dM}$, $\tilde{\Lambda}_0(2) = \Lambda_0(2)/\sigma^L$, and $\tilde{\Lambda}_0(3) = \Lambda_0(3)/\sigma^{CP} - \kappa_{1M}B_M\sigma_s\Lambda_0(1)/(\sigma_{dM}\sigma^{CP})$.

For each asset, we can compute covariances of unexpected returns with the MKT, LVL, and CP shocks inside the model. In the model that first covariance is given by:

$$cov(r^i_{t+1} - E_t[r^i_{t+1}], \varepsilon^{MKT}_{t+1}) = \sigma_{dM}\sigma_{di} + \kappa_{1M}B_M\kappa_{1i}B_i\sigma^2_s.$$

A calibration where $B_M \approx 0$ and $\sigma_{dV} \approx \sigma_{dG}$ will replicate the observed pattern (the linearization constant κ_{1i} will be close to 1 for all portfolios). Second, the covariance of stock portfolio returns with CP shocks is given by:

$$cov(r^i_{t+1} - E_t[r^i_{t+1}], \varepsilon^{CP}_{t+1}) = \kappa_{1i}B_i\sigma_s\sigma^{CP}.$$

The model generates a value premium because of differential exposure to CP shocks when $B_V > B_G$. When $\sigma_{dV} \approx \sigma_{dG}$, the stronger loading of expected dividend growth of value stocks to s_t ($\gamma_{1V} > \gamma_{1G}$) makes $B_V > B_G$. Put differently, in the model -as in the data- returns on value stocks are more exposed to bond risk premium shocks than returns on growth stocks. Third, stock return innovations have a zero covariance with LVL shocks in the model by construction, similar to the small exposures in the data.

Likewise, we can compute covariances of bond return innovations with the MKT, LVL, and CP shocks. In that order, they are:

$$B^\$_n\kappa_{1M}B_M\sigma_s, \quad C^\$_n\sigma_x\sigma^L, \quad B^\$_n\sigma_s\sigma^{CP}.$$

When $B_M \approx 0$, exposure of bond returns to the market factor shocks is close to zero. Exposure to level shocks is negative: an increase in the level of interest rates reduces bond prices and returns. Exposure to CP shocks is also negative: an increase in the bond risk premium reduces bond prices and returns. Both exposures become more negative with the horizon because $B^\$_n$ and $C^\$_n$ increase in absolute value with maturity n.

D.3. Calibration

This section describes our calibration. We start by describing how we define recessions in the model. We construct recessions in the model in a procedure that mimics the NBER dating algorithm and that matches the frequency and duration of recessions. Second, we describe the calibration of dividends and inflation processes. Third, we describe the choice of market price of risk parameters.

Recessions in the Model In order to measure how dividends change over the recession, we have to define recessions in the model. Our algorithm mimics several of the features of the NBER dating procedure: (i) The recession is determined by looking back in time at past real economic activity (s_t in the model) and its start is not known in real time, (ii) there is a minimum recession length, and (iii) it captures the notion that the economy went through a sequence of negative shocks and that economic activity is at a low level. We split each recession into three equal periods and refer to the last month of each period as the first, second, and third stage of the recession. The s process is negative at the start of the recession, falls considerably in the first stage of a recession, continues to fall in the second stage, and partially recovers in the last stage. Our recession dating procedure is novel, matches the empirical distribution of recession duration, and generates interesting asset pricing dynamics during recessions, to which we return to below. We now describe the recession dating procedure in detail.

Recessions in the model are determined by the dynamics of the state process s_t. Define the cumulative shock process $\chi_t \equiv \sum_{k=0}^{K} \varepsilon_{t-k}^{s}$, where the parameter K governs the length of the backward-looking window. Let $\underline{\chi}$ and $\overline{\chi}$ be the p_1^{th} and p_2^{th} percentiles of the distribution of χ_t, respectively, and let $\underline{s}$ be the be the p_3^{th} percentile of the distribution of the s process. Whenever $\chi_t < \underline{\chi}$, we find the first negative shock between $t-K$ and t; say it occurs in month $t-j$. If, in addition, $s_{t-j} < \underline{s}$, we say that the recession started in month $t-j$. We say that the recession ends the fist month that $\chi_{t+i} > \overline{\chi}$, for $i \geq 1$. We assume that a new recession cannot start before the previous one has ended.

We find the recession parameters (K, p_1, p_2, p_3) by matching features of the fifteen recessions in the 1926-2009 data. In particular, we consider the fraction of recession months (19.86% in the data), the average length of a recession (13.3 months), the minimum length of a recession (6 months), the 25^{th} percentile (8 months), the median (11 months), the 75^{th} percentile (14.5 months), and the maximum length (43 months). We simulate the process for s_t for 10,000 months, determine recession months as described above, and calculate the weighted distance between the seven moments in the simulation and in the data. We iterate on the procedure to find the four parameters that minimize the distance between model and data. The weighting matrix is diagonal and takes on the following values: .9, .9, .7, .5, .7, .5, and .5, where the weights are described in the same order as the moments in the text. We use an extensive grid search and limit ourselves to integer values for the parameters. The best fit has 19.70% of months in recession, an average length of 12.0 months, a minimum of 6, 25^{th} percentile of 8, median of 11, 75^{th} percentile of 14, and maximum of 43 months. The corresponding parameters are $K = 7$ months, $p_1 = 17$, $p_2 = 37$, and $p_3 = 29$.

To describe how the variables of interest behave over the course of a recession, it is convenient to divide each recession into three equal stages, and to keep track of the value in the last month of each stage. More precisely, we express the variable in percentage difference from the peak, which is the month before the recession starts. For example, if a recession lasts 9 (10) months, we calculate how much lower dividends are in months 3, 6, and 9 (10) of the recession, in percentage terms relative to peak. Averaging these numbers over recessions indicates the typical change of the variable of interest in three stages of a recession. The third-stage number summarizes the behavior of the variable over the entire course of the recession. We apply this procedure equally to the data and the model simulation.

We set $\rho_s = .9355$ to exactly match the 12-month autocorrelation of the CP factor of .435. This low annual autocorrelation is consistent with the interpretation of s as a business-cycle frequency variable. We set $\sigma_s = 1$; this is an innocuous normalization. The s process is negative at the start of the recession (1.6 standard deviations below the mean), falls considerably in the first stage of a recession (to 3.2 standard deviations below the mean), continues to fall in the second stage (to -3.9 standard deviations), and partially recovers in the last stage (to -2.9 standard deviations).

Dividend and Inflation Parameters We calibrate parameters to match moments of real dividend growth on the market portfolio, value portfolio (fifth book-to-market quintile), and growth portfolio (first quintile) for 1927-2009 (997 months). Since nominal bond yields are unavailable before 1952, we compare our model's output for nominal bond yields and associated returns to the average for 1952-2009. In our model simulation, we reinvest monthly dividends at the risk-free rate to compute an annual real dividend series, replicating the procedure in the data. We calculate annual inflation as the twelve-month sum of log monthly inflation, as in the data.

The most important parameter is γ_{1i}, which measures how sensitive dividend growth is to changes in real economic activity. In light of the empirical evidence presented in Section II.A of the main paper, we choose γ_{1i} to match the log change in annual real dividends between the peak of the cycle and the last month of the recession. In the data, the corresponding change is -21.0% for value stocks (the fifth BM portfolio), + 2.2% for growth stocks (first BM portfolio), and -5.2% for the market portfolio (CRSP value-weighted portfolio). Given the parameters governing the s dynamics and the recession determination described above, the model matches these changes exactly for $\gamma_{1G} = -.4e-4$,

$\gamma_{1V} = 97.6e-4$, and $\gamma_{1M} = 24.8e-4$. Note that $\gamma_{1V} > \gamma_{1G}$ delivers the differential fall of dividends on value and growth stocks. This is the central mechanism behind the value premium.

The rest of the dividend growth parameters are chosen to match the observed mean and volatility. We choose $\gamma_{0G} = .0010$, $\gamma_{0V} = .0044$, and $\gamma_{0M} = .0010$ to exactly match the unconditional mean annual log real dividend growth of 1.23% on growth, 5.26% on value, and 1.23% on the market portfolio. We choose $\sigma_{dM} = 2.09\%$ to exactly match the unconditional volatility of annual log real dividend growth of 10.48%. We set $\sigma_{dG} = 1.94\%$ and $\sigma_{dV} = 2.23\%$ in order to match the fact that the covariance of growth stocks with market return innovations is slightly higher than that of value stocks. However, the difference needs to be small to prevent the value premium from being due to differential exposure to market return shocks. To be precise, this difference makes the contribution of the market factor to the value premium equal to 0.44% per year, the same as in the data. We set the idiosyncratic volatility parameter for growth $\sigma_G = 3.48\%$ to match exactly the 13.75% volatility of dividend growth on growth stocks, given the other parameters. We set $\sigma_V = 10.94\%$ because the volatility of dividend growth on value stocks of 48.93%. The 12-month autocorrelation of annual log real dividend growth in the model results from these parameter choices and is -.01 for G, .21 for V, and .29 for M, close to the observed values of .11, .16, and .29, respectively.

Inflation parameters are chosen to match mean inflation, and the volatility and persistence of nominal bond yields. We choose $\bar{\pi} = .0026$ to exactly match average annual inflation of 3.06%. We choose $\rho_x = .989$ and $\sigma_x = .03894\%$ to match the unconditional volatility and 12-month autocorrelation of nominal bond yields of maturities 1- through 5-years (1952-2009 Fama-Bliss data). In the model, volatilities decline from 3.13% for 1-year to 2.58% for 5-year bonds. In the data, volatilities decline from 2.93% to 2.72%. The 12-month autocorrelations of nominal yields range from .88 to .84 in the model, and from .84 to .90 in the data. Our parameters match the averages of the autocorrelations and volatilities across these maturities. We choose the volatility of unexpected inflation $\sigma_\pi = .7044\%$ to match the volatility of inflation of 4.08% in the data. The 12-month autocorrelation of annual inflation is implied by these parameter choices and is .59 in the model, close to the .61 in the data. We set the real short rate $y = .0018$, or 2.1% per year, to match the mean 1-year nominal bond yield of 5.37% exactly, given all other parameters.

Market Prices of Risk We set $\Lambda_0(1) = .2913$ to match the unconditional equity risk premium on the market portfolio of 7.28% per year (in the 1927-2009 data). The market price of expected inflation risk $\Lambda_0(1) = -.0986$ is set to match the 5-1-year slope of the nominal yield curve of 0.60%. The term structure behaves nicely at longer horizons with 10-year yields equal to 6.27% per year, and 30-year yields equal to 6.49% per year. The average of the annual bond risk premium on 2-year, 3-year, 4-year, and 5-year bond returns, which is the left-hand side variable of the CP regression, is 0.75% in the model compared to 0.87% in the data. The mean CP factor is .0075 in model and .0075 in the data. We set the market price of cyclical risk $\Lambda_0(3) = .0249$ in order to match the 5.22% annual value premium (in the 1927-2009 data).

We set $\Lambda_1(1) = .1208$ in order to generate a slightly negative $B_M = -0.000624$. As argued above, the near-zero B_M prevents the value premium from arising from exposure to market return shocks, and it prevents bond returns from being heavily exposed to market risk. The slight negative sign delivers a slightly positive contribution of exposure to market return shocks to bond excess returns, as in the data. In particular, it generates a 15 basis point spread between ten-year and 1-year bond risk premia coming from market exposure, close to the 30 basis points in the post-1952 data. Finally, we set $\Lambda_1(2) = -0.0702$ in order to exactly match the volatility of the CP factor of 1.55%. The volatility of the average annual bond risk premium on 2-year, 3-year, 4-year, and 5-year bonds is 3.93% in the model and 3.72% in the data. As mentioned above, ρ_s is chosen to match the persistence of CP. Thus the model replicates the mean, volatility, and persistence of the CP factor and the nominal bond risk premium. The maximum annualized log Sharpe ratio implied by the model, $E[\sqrt{\Lambda_t'\Lambda_t}]\sqrt{(12)}$ is 1.44. Unfortunately, there is no easy comparison with the numbers in the empirical section (bottom panel of Table 1).

Risk Premium Decomposition The main result from the calibration exercise is that we are able to replicate the three-factor risk premium decomposition we uncovered in Section 3. Figure A.9 is the model's counterpart to Figure 5 in the data. It shows a good quantitative match for the relative contribution of each of the three sources of risk to the risk premia for growth, value, and market equity portfolios, as well as for maturity-sorted government bond portfolios. This fit is not a forgone conclusion, but results from the richness of the model and the choice of parameters. For example, differential exposure to the market factor could have well been the source of the value risk premium in the model given that the market shocks are linear combinations of permanent dividend growth and transitory cyclical shocks. Or, bonds of different maturity could have differential exposure to the market factor shocks. The data show no heterogeneity in both types of exposures. The model has just enough richness to replicate these patterns.

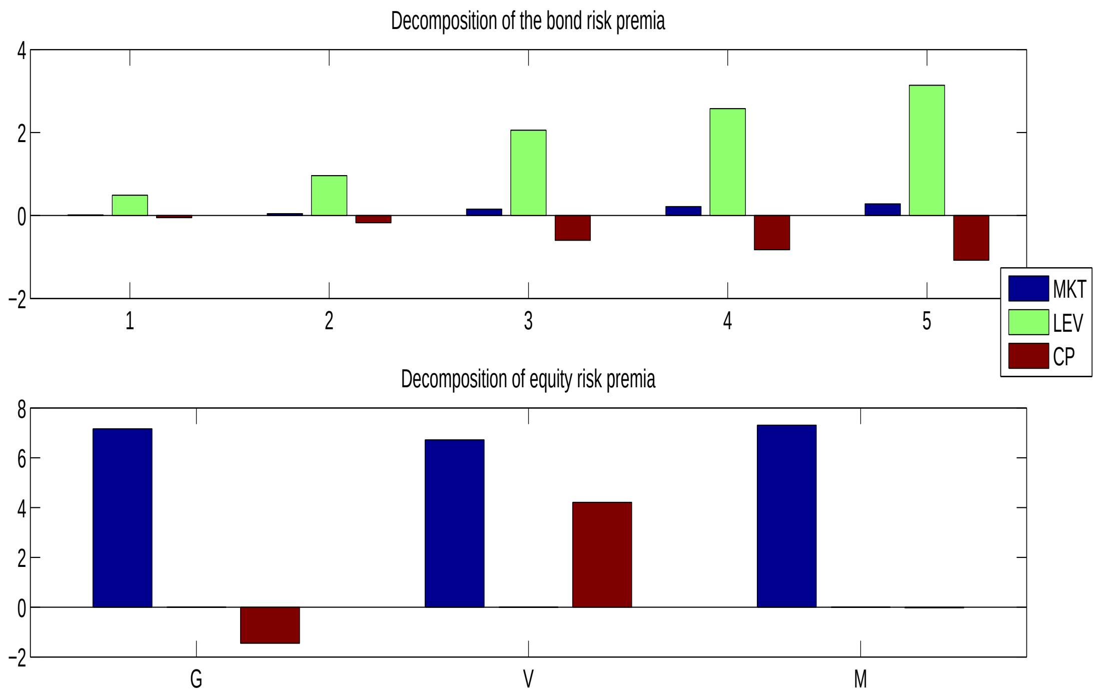

Figure A.9: Decomposition of annualized excess returns in model.

The figure plots the risk premium (expected excess return) decomposition into risk compensation for exposure to the CP factor, the LVLfactor, and the MKT factor. Risk premia, plotted against the left axis, are expressed in percent per year. The top panel is for the five bond portfolios (1-yr, 2-yr, 5-yr, 7-yr, and 10-yr) whereas the bottom panel is for growth (G), value (V), and market (M) stock portfolios. The results are computed from a 10,000 month model simulation under the calibration described in detail in Appendix D.3.

We conclude that the model delivers a structural interpretation for the MKT, LVL, and CP shocks. CP shocks reflect (transitory) cyclical shocks to the real economy, which naturally carry a positive price of risk. The LVL shock captures an expected inflation shock, and the MKT shock mostly captures a (permanent) dividend growth shock. The model quantitatively replicates the unconditional risk premium on growth, value, and market equity portfolios, and bond portfolios of various maturities, as well as the decomposition of these risk premia in terms of their MKT, LVL, and CP shock exposures. Furthermore, it matches some simple features of nominal term structure of interest rates and bond risk premia. It does so for plausibly calibrated dividend growth and inflation processes.

D.4. Asset Pricing Dynamics over the Cycle

Finally, our model implies interesting asset pricing dynamics over the cycle. The CP factor, or nominal bond risk premium, starts out negative at the start of the recession, falls substantially in the first stage of the recession, falls slightly more in the second stage, before increasing substantially in the third stage of the recession. This pattern for bond risk premia is reflected in realized bond returns. In particular, the negative risk premium shocks at the start of a recession increase bond prices and returns, and more so on long-term than short-term bonds. An investment of $100 made at the peak in a portfolio that goes long the 30-year and short the 3-month nominal bond gains $8.0 in the first stage of the recession. The gain further increases to $11.7 in the second stage, before falling back to a $7.4 gain by the last month of the recession. The latter increase occurs as consequence of the rising bond risk premium. Taken over the entire recession, long bonds gain in value so that they are recession hedges Campbell, Sunderam, and Viceira (2012). The same is true in the data, where the gain on long-short bond position is $6.1 by the last month of the recession. Value stocks are risky in the model. Their price-dividend ratio falls by 21% in the first stage compared to peak, continues to fall to -34%, before recovering to -29% by the end of the recession. In the data, the pd ratio on value stocks similarly falls by 16% in the first stage, falls further to -26%, before recovering to +4%. Value stocks perform poorly, losing more during the recession than growth stocks, both in the model and in the data.

One important feature the model (deliberately) abstracts from are discount rate shocks to the stock market. As a result, the price-dividend ratio and stock return are insufficiently volatile and reflect mostly cash-flow risk. While obviously counter-factual, this assumption is made to keep the exposition focussed on the main, new channel: time variation in the bond risk premium, the exposure to cyclical risk, and its relationship to the value risk premium. One could write down a richer model to address this issues, but only at the cost of making the model more complicated. Such a model would feature a market price of aggregate dividend risk which varies with some state variable z. The latter would follow an AR(1) process with high persistence, as in Lettau and Wachter (2009). All price-dividend ratios and expected stock returns would become more volatile and more persistent, generating a difference between the business-cycle frequency behavior of the bond risk premium and the generational-frequency behavior of the pd ratio. This state variable could differentially affect value and growth stocks, potentially lead to a stronger increase in the pd ratio of value than that of growth in the last stage of a recession. This would shrink the cumulative return gap between value and growth stocks during recessions, which the model now overstates.