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The cross-section and time series of stock and bond returns

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ABSTRACT

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-market 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 book-to-market-sorted portfolios of stocks and maturity-sorted bond portfolios, while reproducing the time-series variation in expected bond returns. The business cycle itself is a priced state variable in stock and bond markets.

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 et al., 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. It studies a much longer sample with more adverse macroeconomic events than previously examined (1926–2012 compared to 1968–1989 in Lakonishok et al. (1994), or 15 recessions compared to 4). The paper develops and applies 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 at business cycle horizons: the Cochrane–Piazzesi factor (*CP*, Cochrane and Piazzesi, 2005), the slope of the term structure, and the best yield-based linear predictor

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of economic activity at the one-year horizon. 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 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. This pattern of exposures is 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. 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. The paper also shows that periods in which the bond factors are low are periods of significantly lower future dividend growth rates on the market portfolio and on the value-minus-growth portfolio.

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, labeled "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. The 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 5.04% per year in a risk-neutral benchmark economy to 0.49% 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.

The results are robust for different sub-samples and different sets of test assets. The model prices a set of corporate bond portfolios sorted by credit rating, jointly with equity and government bond portfolios. While it prices several other equity portfolio sorts, the model cannot explain the cross-section of momentum or return-to-equity portfolios.

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. Our parsimonious stochastic discount factor model makes progress towards a unified pricing model of stock and bond markets.

Furthering this connection, the last part of the paper sets up and solves a simple dynamic asset pricing model that can account for the empirical facts and that lends a structural interpretation to the three priced sources of risk. Shocks to the bond risk premium are shocks to a leading indicator of the business cycle, level shocks are expected inflation shocks, and market shocks reflect compensation for dividend growth risk.

The rest of the paper is organized as follows. Section 1 discusses the related literature. 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 documents the robustness of our results to other test assets and estimation methods. Section 5 contains a simple asset pricing model that formalizes the connections between the bond risk premium, the value premium, and the macro-economy. Section 6 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 (2007, 2011) 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). This literature has focused on explaining the cross-section of stock returns. Other notable contributions linking the cross-section of stock returns to firm characteristics in the production-based asset pricing literature are Berk et al. (1999), Gomes et al. (2003), Papanikolaou (2011), Liu et al. (2009),

[1] Examples are Bakshi and Chen (2005) and Bekaert et al. (2009) in a Gaussian setting and Campbell et al. (2017) in a linear-quadratic model. Lustig et al. (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.

Kogan and Papanikolaou (2014), and Hou et al. (2015). We are unaware of work in this area that also accounts for the cross-section of Treasury and corporate bond returns.

The business cycle itself plays a secondary role in modern dynamic asset pricing theory.[2] This paper uncovers 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 et al. (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 et al. (2004) analyze an ICAPM model in which the real rate, expected inflation, and the Sharpe ratio dynamically change 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 et al. (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 their 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

This section documents that value stocks suffer from bad cash-flow shocks at times when a representative investor experiences 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 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, we explore the robustness to other yield-curve variables in Appendix A.

2.1. Cash-flow risk in value-growth and the business cycle

The analysis uses monthly data from the Center for Research on Securities Prices (CRSP) on dividends and inflation from July 1926 until December 2015. 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. The focus is on cash dividends.[5] It is important to note

[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 et al., 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 et al. (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 (2015), and Bansal and Shaliastovich (2013), while Hansen et al. (2008) study the implications for the cross-section of equity portfolios.

[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 et al., 2008). An alternative is to include share repurchases to cash dividends, but this would correspond to a different dynamic strategy

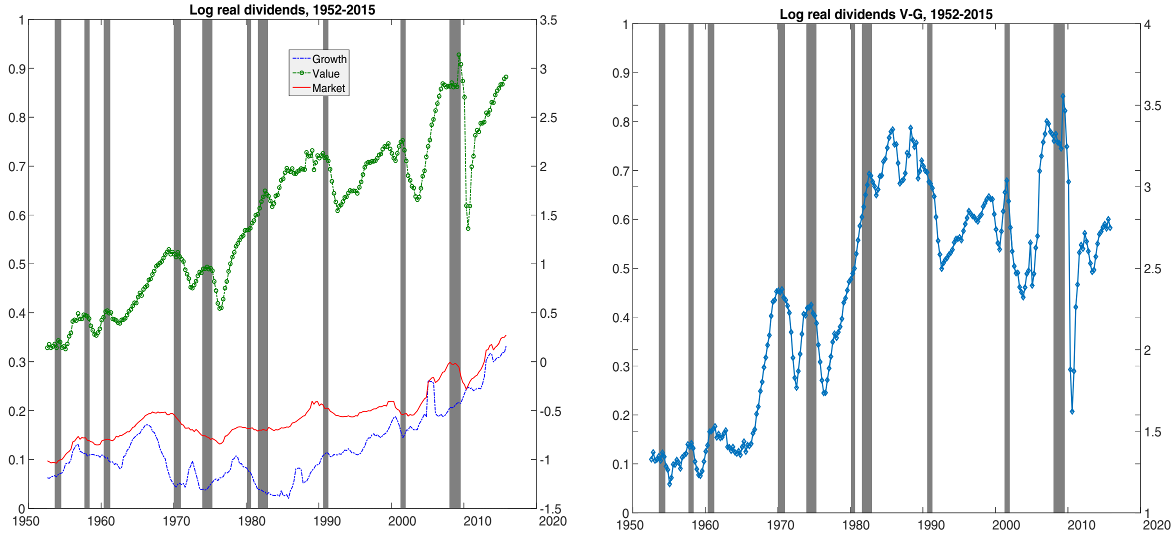

Fig. 1. Dividends on value, growth, and market portfolios. The left panel shows the log real dividend on book-to-market quintile portfolios 1 (growth, dashed line with squares) and 5 (value, dotted line with circles) and on the CRSP value-weighted market portfolio, plotted against the right axis. The right panel shows the log real dividend on book-to-market quintile portfolios 5 (value) minus the log real dividend on the book-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 2015 and are sampled every three months in the figure.

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), 3.4% (2), 3.8% (3), 3.9% (4), and 3.0% (5). The market portfolio has an average dividend yield of 3.3%. Additional summary statistics for variables in this section are reported in Appendix A.

In the left panel of Fig. 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 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). Strictly adhering to the NBER recession dates understates the change in dividends from the highest to their lowest point over the cycle. The right panel of Fig. 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]

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. The *CP* factor is the linear combination of 2- through 5-year government bond yields that bests forecasts future excess bond returns, and follows the construction in Cochrane and Piazzesi (2005).[7] Appendix A shows that these results extend to two alternative linear combinations: the

(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.

[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 2015, 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

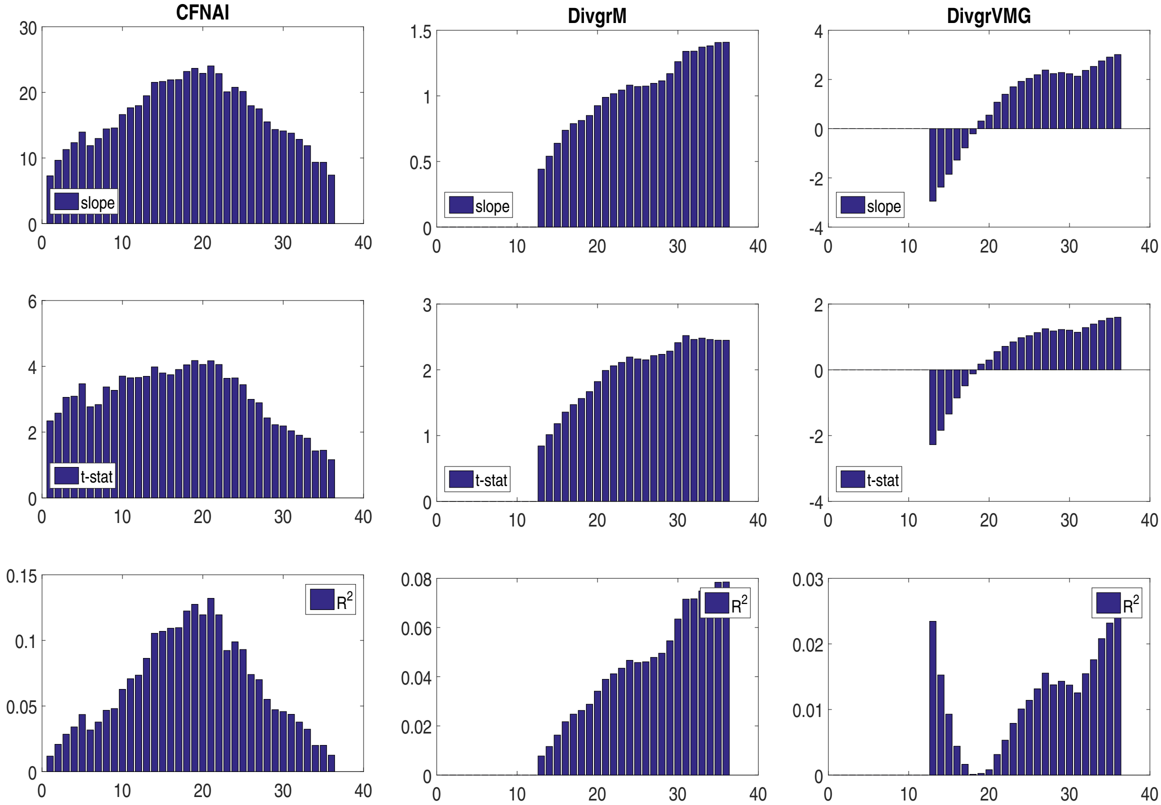

Fig. 2. Economic activity predicted by bond factors. We consider a regression of future values of *CFNAI*, which we normalize to have mean zero and standard deviation one, on the current *CP* factor: $CFNAI_{t+k} = c_k + \beta_k CP_t + \varepsilon_{t+k}$, where k is the forecast horizon expressed in months. The regressions are estimated by OLS and we calculate Newey–West standard errors with $k-1$ lags. The top panel displays the predictive coefficient β_k, the middle panel the t-statistic, and the bottom panel the corresponding R^2. We consider $k = 1, \ldots, 36$ 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 2015.

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 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 2015, dictated by data availability. The left panels in Fig. 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*

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 10.7% R^2 of the five-year minus one-year yield spread, another well-known bond return predictor.

[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) show 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 et al. (2014) incorporate this finding in an affine term structure model. Ludvigson and Ng (2009) show 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 trough. 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.

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, with a t-statistic of 4.2 and an R^2 of 13.2%. This maximum predictability is for *CFNAI* 21 months later. From Fig. 2 we infer that a high *CP* factor precedes higher economic activity about 12–24 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 regressions like Eq. (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 Fig. 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, although the statistical significance is weaker. The predictability of *CP* is concentrated at longer horizons of 33–36 months ahead. Table A.II in the Appendix contains the point estimates. This regression evidence implies that the bond market 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 is fragile because the lead-lag pattern may fluctuate from one recession to the next (see Fig. 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. Fig. 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 Fig. 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 top left panel of Fig. 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, +1, and +2, *CP* rises sharply. This figure shows that realized returns on the value-minus-growth strategy are negative in quarter -1 and 0 and but rise in quarters +1 and +2 (at which point they are slightly positive once we add back in the 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 Fig. 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 bottom left panel of Fig. 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 afterwards. This decline in value-minus-growth dividend growth is persistent and economically large. 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 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

[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.

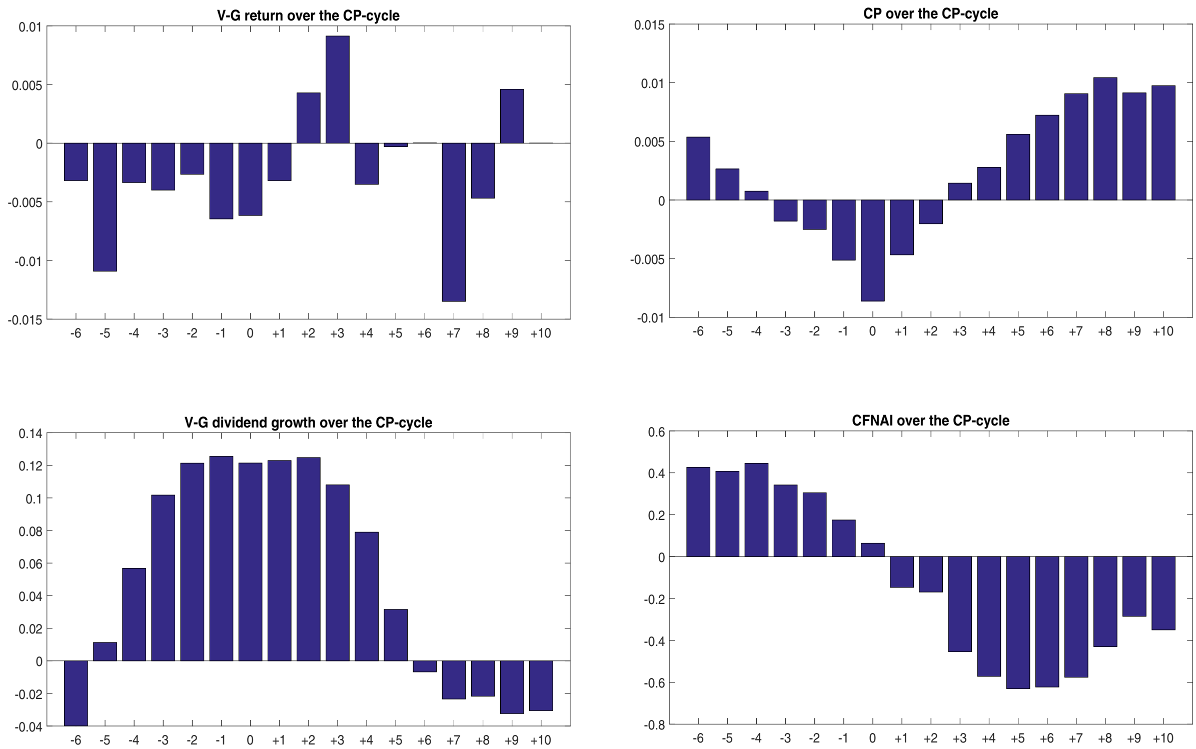

Fig. 3. Low *CP* events. The figure shows four quarterly series in event time. The event is defined as a quarter in which the quarterly *CP* factor in its respective lowest 25% of observations. This selection leads to 63 events out of 254 quarters. The sample runs from 1953.Q3 until 2015.Q4. In each 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.

average (*CFNAI* is close to zero). *CFNAI* then turns negative for the next ten quarters, bottoming out five to seven 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 one standard deviation of *CFNAI*. The appendix shows similarly strong dynamics in real GDP growth around low-*CP* events.

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 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 41 events out of 254 quarters (or about 16% of the sample). The top left panel of Fig. 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 around 8% below the quarterly mean.

The top right panel of Fig. 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 capture 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. Between the end of quarters 1 and 10, cumulative dividend growth on value-minus-growth is −52.2%, on average across low-value events. This finding dovetails nicely with the fall in dividends on value-minus-growth over

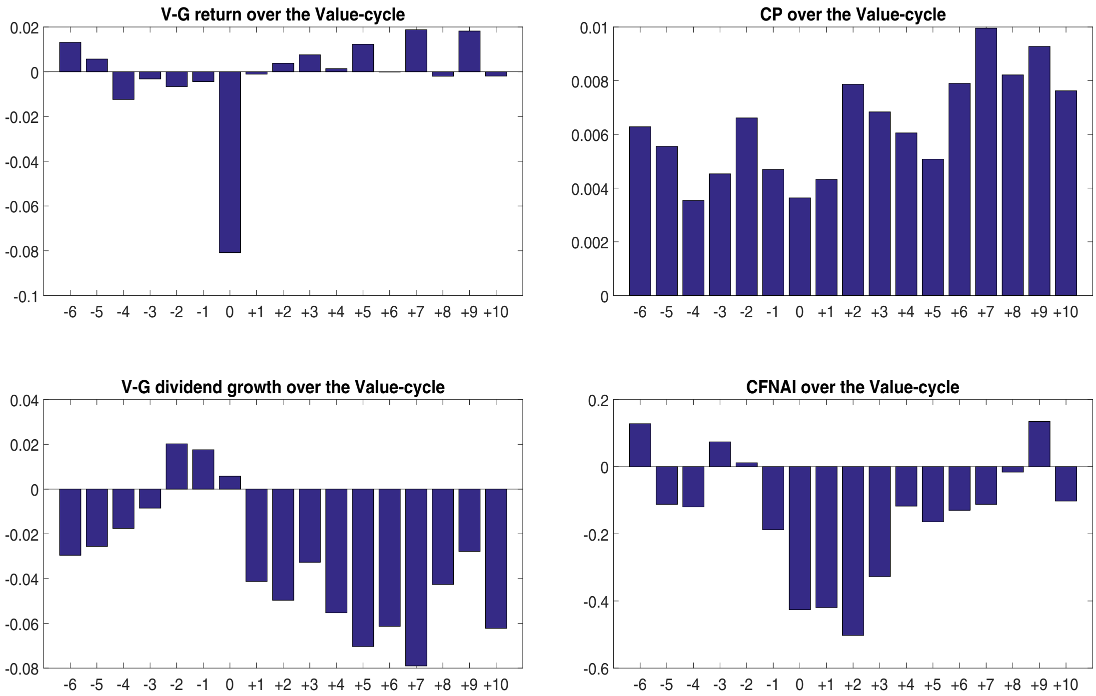

Fig. 4. Low-value events. The figure shows four quarterly series in event time. An event is defined as a quarter in which both the realized log real return on the fifth book-to-market portfolio (value) and the realized log return on value-minus-growth (first book-to-market portfolio) are in their respective lowest 30% of observations. The sample runs from 1953.Q3 until 2015.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.

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 Fig. 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 0.5 standard deviations of *CFNAI*. The Appendix shows a similar effect using real GDP growth as a measure of economic activity. 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 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 an 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. Section 5 presents a structural asset pricing model, which starts from cash flow growth rather than returns, and formalizes the intuition for the empirical connection between dividends and prices of stocks, bond prices, and the business cycle.

3.1. Setup

Let P_t be the price of a risky asset, D_{t+1} its dividend, 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 follows a first-order vector-autoregression with companion matrix Γ and conditionally normally, i.i.d. distributed innovations $\varepsilon_t \sim \mathcal{N}(0, \Sigma)$:

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

$$\Lambda_t = \lambda_0 + \lambda_1 CP^{\star}_t, \tag{4}$$

where $CP^{\star}_t$ denotes the demeaned CP factor. 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 $N \times 1$ vector that governs the time variation in the prices of risk. In Appendix D, we provide a formal specification analysis to determine the order of the VAR. We also show that our asset pricing results are robust to changing the model to a second- or third-order VAR.

Log returns on an asset j can be stated as the sum of expected and unexpected returns: $r^j_{t+1} = E_t[r^j_{t+1}] + \eta^j_{t+1}$. Unexpected log returns η^j_{t+1} 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 including a Jensen adjustment:

$$rx^j_{t+1} \equiv r^j_{t+1} - y^{\$}_t(1) + \frac{1}{2}V[\eta^j_{t+1}].$$

The no-arbitrage condition then implies:

$$E_t\left[rx^j_{t+1}\right] = Cov_t\left[rx^j_{t+1}, -m^{\$}_{t+1}\right] = Cov\left[\eta^j_{t+1}, \varepsilon'_{t+1}\right]\Lambda_t \equiv \Sigma_{Xj}(\lambda_0 + \lambda_1 CP^{\star}_t). \tag{5}$$

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

$$E\left[rx^j_{t+1}\right] = \Sigma_{Xj}\lambda_0. \tag{6}$$

The main object of interest, λ_0, is estimated below. Eq. (6) suggests an interpretation of our model as a simple factor model, where the factor innovations ε are the priced sources of risk. Alternatively, we can rewrite (6) to a beta representation where expected returns are decomposed in betas multiplied by factor risk premia. To focus on the pricing of individual shocks, we prefer to estimate the pricing model in (6). Lastly, we assume in (6) that second moment of returns and pricing innovations are constant. In Appendix E, we show that our results are robust to allowing for time-varying second moments.

3.2. Data and implementation

The main asset pricing result 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-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 2015 (762 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 2015, which restricts our estimation to this sample (432 observations). Section 4 examines other sets of test assets for robustness. We include three asset pricing factors in the state vector 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 following Cochrane and Piazzesi (2008). The third factor, MKT, is the value-weighted stock market return from CRSP.

The unexpected bond returns in η are constructed as the residuals from a regression of each bond portfolio's log excess return on the lagged CP factor. Similarly, stock returns are also assumed to be predictable by the lagged CP factor, and the unexpected stock returns in η are constructed as the residual from a regression of each stock portfolio's log excess return on the lagged CP factor.

We impose an autoregressive structure on the state vector X_t and 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

Table 1
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. To construct the factor-mimicking portfolio, we regress *CP* innovations on a set of excess returns, R_t^e, $\epsilon_t^{CP} = \nu_0 + \nu_1' R_t^e + u_t$. We use 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 last row of Panel A reports the mean absolute pricing error across all 11 test assets (MAPE). Panel B reports the estimates of the 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 2015.

Panel A: Pricing Errors (in % per year)							
	(1) RN SDF	(2) *CP* SDF	(3) *LVL*	(4) *LVL* only bonds	(5) *MKT*	(6) *LVL, MKT*	(7) *MKT, SMB, HML*
10-yr	1.74	0.20	−3.77	−0.41	1.34	−0.40	0.68
7-yr	2.03	0.41	−2.86	0.12	1.74	0.20	1.16
5-yr	1.69	−0.22	−2.44	0.08	1.49	0.18	1.01
2-yr	1.19	−0.73	−0.83	0.40	1.04	0.40	0.82
1-yr	0.94	−0.49	−0.10	0.53	0.83	0.51	0.72
Market	6.83	−0.79	5.66	6.37	−1.33	−1.29	−0.12
BM1	6.49	−0.20	5.27	6.01	−2.02	−1.98	0.43
BM2	7.20	−0.19	5.90	6.69	−0.77	−0.78	−0.44
BM3	8.24	0.90	6.86	7.70	0.96	0.89	−0.34
BM4	8.43	−0.45	7.14	7.92	0.85	0.83	−1.07
BM5	10.64	0.79	9.92	10.36	2.30	2.49	1.25
MAPE	5.04	0.49	4.61	4.24	1.33	0.90	0.73
Panel B: Prices of Risk Estimates λ_0							
MKT		2.60			3.71	3.52	5.43
LVL/SMB		−18.90	−32.95	−12.88		−10.52	−8.02
CP/HML		85.63					5.97
Panel C: Test on Risk Prices and Pricing Errors							
$H_0 : \lambda_0 = 0$, p-value (%)		0.11	0.00		0.02	0.01	0.01
H_0 : Pr. error $= 0$, p-value (%)		0.69	0.00		0.00	0.00	0.01

innovation correlations between our three factors are close to zero. We find correlations of 0.05 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 0.9% and 2.0% per year and tend to increase in maturity. The aggregate excess stock market return is 6.8%, the excess returns on the book-to-market portfolios range from 6.5% (BM1, growth stocks) to 10.6% (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 1980–2015 sample. Average excess returns on long-dated government bonds are substantially higher in this sample, for example 3.7% per year for the 10-year bond. The equity risk premium is also slightly higher at 7.3% while the value risk premium is slightly lower at 3.5% per year. The rating-sorted corporate bond portfolios have average excess returns between 3.5% per year for the highest-rated portfolio (AAA) and 4.3% for the lowest-rated portfolio (BBB).

The three risk price parameters in $\hat{\lambda}_0$ are estimated by minimizing the sum of squared pricing errors on the $J = 11$ test assets in Table 1. Formally, we define the GMM moments, conditional on the second moment matrix Σ_{Xj}, as:

$$g_T(\Lambda_0) = E_T\left[rx_{t+1}^j\right] - \Sigma_{Xj}\lambda_0, \tag{7}$$

where $E_T[\,\cdot\,]$ denotes the sample average. We estimate λ_0 as:

$$\widehat{\lambda}_0 = argmin_{\lambda_0}\ g_T(\lambda_0)' g_T(\lambda_0), \tag{8}$$

Table 2
SDF model for stocks, treasuries, and corporate bonds. The table is similar to Table 1 except that the sample is January 1980 until December 2015. 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) *CP* SDF	(3) *CP* SDF not re-estim.	(4) *CP* SDF	(5) *MKT, SMB, HML*
10-yr	3.69	0.18	0.18	0.44	0.24
7-yr	3.58	0.18	0.18	0.44	0.80
5-yr	2.91	−0.06	−0.06	0.17	0.89
2-yr	1.75	−0.27	−0.27	−0.11	0.85
1-yr	1.18	−0.05	−0.05	0.04	0.77
Market	7.33	−1.06	−1.06	−1.08	0.44
BM1	7.47	−0.17	−0.17	−0.28	0.49
BM2	8.57	0.56	0.56	0.53	−0.59
BM3	8.37	0.66	0.66	0.66	−2.02
BM4	7.84	−1.39	−1.39	−1.26	−2.17
BM5	10.97	1.36	1.36	1.46	2.78
Credit1	3.50		−0.76	−0.46	0.98
Credit2	3.64		−0.63	−0.34	0.94
Credit3	3.92		−0.50	−0.22	1.31
Credit4	4.31		−0.16	0.10	1.99
MAPE	5.27	0.54	0.53	0.51	1.15
Panel B: Prices of Risk Estimates λ_0					
MKT		2.73	2.73	2.80	6.42
LVL/SMB		−22.20	−22.20	−20.35	−19.68
CP/HML		45.64	45.64	41.70	2.88
Panel C: Test on Risk Prices and Pricing Errors					
$H_0 : \lambda_0 = 0$, p-value (%)		0.55		0.68	0.41
H_0 : Pr. error $= 0$, p-value (%)		2.66		2.26	1.37

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. We estimate the risk prices of all the other models in the same way.[11]

Having estimated the constant market prices of risk, λ_0, we turn to the estimation of the vector λ_1, which governs the time variation in the prices of risk. The vector λ_1 is chosen to exactly match the observed predictability of the stock market and the average bond return by the *CP* factor as documented by Cochrane and Piazzesi (2005).[12] Specifically, 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 either *CP* (benchmark case), the slope of the yield curve or one of the other bond factors that we consider in the appendix. We do not find strong evidence that the value-minus-growth portfolio returns are predicted by the *CP* factor, and we therefore set $\lambda_{1(1)} = 0$.

We use two predictive regressions to pin down this variation in risk prices. We regress excess returns on a constant and lagged *Z*:

$$rx^j_{t+1} = a_j + b_j Z_t + \eta^j_{t+1},$$

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

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

[11] As is the case for two-pass regressions, the risk price may deviate from the in-sample mean of traded factors, such as the market factor. 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.

[12] Time variation in the market prices of risk drives time variation in expected returns, thereby affecting the unexpected returns η^j_{t+1} and the unconditional asset pricing model in Eq. (6). Cochrane and Piazzesi (2005) provide evidence of predictability of the aggregate market return by the lagged *CP* factor. In addition, we could include the aggregate dividend-price ratio 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*, the dividend-price ratio, both, or no predictability at all. But whatever predictability there is via *CP*, we match it through the estimate of λ_1.

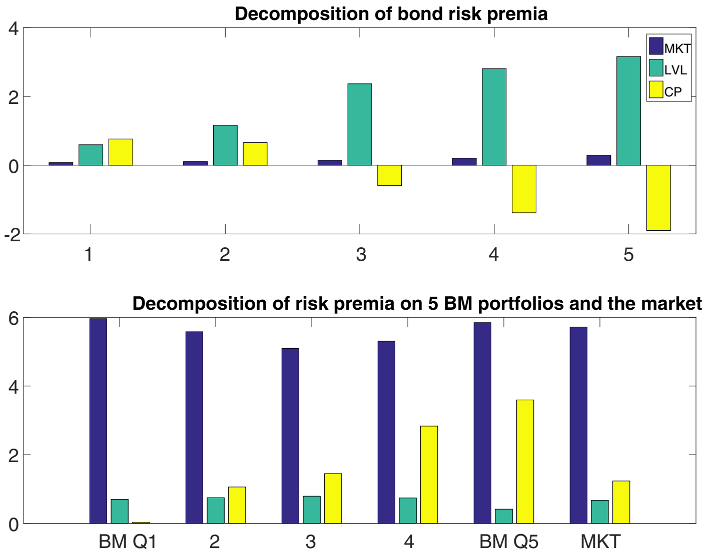

Fig. 5. Decomposition of annualized excess returns in data. The figure plots the risk premium (expected excess return) decomposition into risk compensation for exposure to the *MKT*, *LVL*, and *CP* factors. Risk premia, plotted against the left axis, are expressed in percent per year. The top panel 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 risk exposures times the risk price for each of the three factors. The data are monthly from June 1952 until December 2015.

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 49 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 99 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 B of Table 1 shows the point estimates for λ_0. To obtain risk premia, the risk prices need to be multiplied with the covariance of return and pricing factor innovations, see (6). We estimate a positive price of *CP* risk, 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 32.24 for the *CP* factor price (point estimate of 85.63), 8.15 for the *LVL* factor price (−18.90), and 1.17 for the *MKT* factor price (2.60). Hence, all risk prices are significant at the 5% level.

The first row of Panel C in Table 1 tests the null hypothesis that the market price of risk parameters are jointly zero. This null hypothesis is strongly rejected, with p-value of 0.11%. The last row reports the p-value for the chi-squared test that all pricing errors are jointly zero. All models considered in Table 1 are rejected at the 1% level. However, 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.

Following the separate estimation procedure for λ_1 in the full sample, we find $\hat{\lambda}_{1(2)} = -995$ and $\hat{\lambda}_{1(3)} = 42$ 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 $\hat{\lambda}_{1(2)} = -793$ and $\hat{\lambda}_{1(3)} = 120$ when the predictor is the yield spread ($Z = YSP$).

How does our three-factor model manage to price the cross-section of returns on these test assets? Fig. 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).

The top panel of Fig. 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 standard duration effect. But bonds also have a negative exposure to *CP* shocks for longer-maturity bonds. *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 provides 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 exposed to the *CP* factor, while the stock portfolios are not exposed to the *LVL* factor. The example in Appendix C underscores the challenges in finding a model with consistent risk prices across stocks and bonds, or put differently, the challenge of going from a single asset class to multiple asset classes. In this setting, consistent risk pricing across stocks and bonds only works if the exposures of maturity-sorted bond portfolios to *CP* are linear in maturity. This linearity is what allows the model to jointly price stocks and bonds, but it is not a foregone conclusion.

The bottom panel of Fig. 5 shows that all book-to-market portfolios have about equal exposure to both *MKT* and *LVL* shocks. If anything, 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.

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. 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 4.6%. All pricing errors on the stock portfolios are large and positive, there is a 4.7% 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, that is, 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 confirms that the bond pricing errors fall substantially: The mean absolute bond pricing error goes from 200 bps in column (3) to 31 bps in column (4). However, the overall MAPE remains high at 4.24%. 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 market model where the only non-zero price of risk is the one corresponding to the *MKT* factor. Column (5) of Table 1 reports the corresponding pricing errors. Not surprisingly, this model is unable to jointly price stock and bond returns. The MAPE is 1.33%. One valuable feature is that the aggregate market portfolio is priced reasonably well and the pricing errors of book-to-market portfolio returns are centered around zero. Our estimation procedure does not impose that the *MKT* factor is priced exactly, explaining the 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 intact. The MAPE is 90 bps, which highlights the need for the *CP* factor as a third priced factor.

Column (7) in Table 1 reports results for a three-factor model that includes the market, *SMB*, and *HML* factors (Fama and French, 1992), which offers a better-performing alternative to a model with the *MKT* only to price the cross-section of stocks. The model's MAPE is 73 bps. The 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]

Table A.IV in Appendix B shows that our model prices the bond portfolios and the market portfolio alongside the size deciles, the earnings-price deciles, and the 5-by-5 size and value portfolios using data from Ken French from June 1952 to December 2015. The results are qualitatively similar.

3.4. 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. In standard credit models, corporate bonds are a combination of risk-free bonds and equity. Lower-rated bonds, which are closer to default, have a larger equity component, while highly-rated bonds have a smaller equity component. Based on this logic, 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 54 bps, nearly identical to the 49 bps in the full sample. 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 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. As before, we reject the null that all pricing errors are jointly zero.

The third column adds the credit portfolios. 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 51 bps per year, compared to excess returns of almost 4% per year under risk-neutral pricing. The mean absolute pricing error among all fifteen test assets is 53 bps per year in column (3), which is virtually the same as without the corporate bond portfolios (54 bps per year).

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 28 bps per year and the overall MAPE on all 15 assets is 51 bps per year, 3 bps below the MAPE when corporate bonds are not considered, and 2 basis points less than when the corporate bonds were not included in the estimation. Higher exposures to *CP* innovations and *MKT* innovations both contribute to higher average returns on the lowest-rated credit portfolio.

The last column of Table 2 reports results for the three-factor model with the *MKT*, *SMB*, and *HML* factors. Its pricing errors are higher than in our three-factor model; the MAPE is 1.15%. Average pricing errors on the corporate bond portfolios are 1.31% per year. The model severely underprices the BBB-rated portfolio (Credit4).

3.5. 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. Other linear combinations of these yields may better predict economic activity. Similarly, other linear combinations of yields may 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. 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 77% with *YSP*, 56% with *YGR*, and 76% 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.II and A.III.

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 3. The model with the yield spread factor produces results broadly consistent with those for *CP*. It leads to a larger MAPE of 62 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. Over the 1980–2015 sample, the MAPE is 68 bps (column 2). When we add the corporate bond portfolios, the MAPE falls further to 58 bps and we fail to reject the null hypothesis that all pricing errors are jointly zero at the 5% level.

[13] We find that the price of *SMB* risk is negative, which arises because this risk price cannot be estimated precisely from the five book-to-market portfolios, five bond portfolios, and the equity market portfolio. In Appendix B, we show that once we include portfolios sorted on market capitalization, the price of *SMB* risk turns positive.

Table 3
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. The first, fourth, and seventh columns are for the full 1952–2015 sample, while the other columns are for the 1980–2015 sub-sample in which we observe corporate bond returns.

Panel A: Pricing Errors (% per year)									
	(1) YSP SDF	(2)	(3)	(4) YGR SDF	(5)	(6)	(7) YAP SDF	(8)	(9)
10-yr	0.50	0.69	0.91	0.26	0.52	0.84	−0.17	0.32	0.76
7-yr	0.29	0.18	0.47	0.28	0.05	0.63	0.32	0.11	0.63
5-yr	−0.36	−0.42	−0.11	−0.13	−0.09	0.44	−0.05	0.00	0.45
2-yr	−0.96	−0.80	−0.54	−0.53	−0.75	−0.09	−0.03	−0.81	−0.30
1-yr	−0.68	−0.45	−0.28	−0.73	−0.55	−0.04	−0.04	−0.23	0.05
Market	−0.86	−1.14	−1.16	−0.81	−1.14	−1.21	−0.73	−1.13	−1.17
BM1	−0.60	−0.72	−0.81	−0.03	0.15	−0.50	−0.07	0.31	−0.15
BM2	−0.49	0.37	0.34	−1.29	0.00	0.05	0.00	0.05	0.07
BM3	0.99	0.78	0.76	0.63	0.21	0.34	0.93	−0.19	0.01
BM4	0.27	−0.59	−0.51	0.40	−0.43	−0.26	−1.02	0.00	0.01
BM5	0.82	1.36	1.51	1.14	1.18	1.77	0.90	0.95	1.39
Credit1			−0.42			−0.66			−0.59
Credit2			−0.44			−0.53			−0.57
Credit3			−0.34			−0.63			−0.48
Credit4			0.18			−0.08			−0.16
MAPE	0.62	0.68	0.58	0.57	0.46	0.54	0.39	0.37	0.45
Panel B: Prices of Risk Estimates λ_0									
MKT	2.42	3.16	3.21	1.48	2.68	2.99	2.93	2.84	3.00
LVL	−6.61	−16.52	−15.03	−3.32	−11.89	−11.07	−14.62	−30.26	−24.17
YSP/YGR/YAP	93.20	62.78	55.21	115.95	83.50	50.45	60.83	129.58	96.12
Panel C: Test on Risk Prices and Pricing Errors									
$H_0 : \lambda_0 = 0$, p-value (%)	0.02	0.23	0.27	1.51	2.97	1.27	0.44	9.66	5.65
H_0 : Pr. error $= 0$, p-value (%)	0.72	4.35	5.74	18.67	34.05	20.24	4.16	23.18	7.36

In the next three columns of Table 3 we use *YGR* alongside the *MKT* and *LVL* factors in our asset pricing exercise. This model generates a MAPE of 57 bps for the full sample, 46 bps for the post-1980 sample, and 54 bps when we include the credit portfolios. In all three exercises, we cannot reject the null hypothesis that all pricing errors are zero. 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.

The last three columns show that we can lower MAPE to a mere 39 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 37 bps for the post-1980 sample, and 45 bps for the same sample with credit portfolios. The 76% correlation of *CP* with *YAP* helps to explain why our main pricing results are strong.

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. Robustness

In this section, we confirm the robustness of our asset pricing results. First, we consider other cross-sections of stock returns to be priced alongside bonds. We also verify robustness to using the Fama–MacBeth methodology.

4.1. Other test assets

In addition to the credit portfolios discussed above, we consider several other cross-sections of stock returns. We focus this exercise on the sample January 1967 until December 2015, which is the longest sample for which all factor returns are available. The columns labeled RN in Table 4 report the average returns that need to be explained in this sample. In columns (1)–(5), we consider the 5 bond portfolios, the aggregate stock market, and 10 book-to-market portfolios. In columns (6)–(10), we add 10 portfolios sorted on market capitalization (size). In column (11)–(15), we also add 10 momentum portfolios constructed by Hou et al. (2015).

Table 4
Pricing errors and MPR - book-to-market, size, and momentum deciles. This table reports pricing errors on 10 book-to-market sorted stock portfolios, the value-weighted market portfolio, and five bond portfolios of maturities 1, 2, 5, 7, and 10 years in columns (1)–(5). In columns (6)–(10), we add 10 size-sorted portfolios. In columns (11)–(15), we add 10 momentum portfolios. Pricing errors are expressed in percent per year (monthly numbers multiplied by 1200). We also report the mean absolute pricing error across all securities (MAPE) and estimates of the prices of risk. We compare our model extended with the *UMD* factor, the Carhart model, the model of Hou et al. (2015) (HXZ4), and the 5-factor model of Fama and French (2015) (FF5). Panel C reports asset pricing tests that either all risk prices are zero (top row) or that all pricing errors are zero (bottom row). The sample is from January 1967 to December 2015.

Panel A: Pricing Errors (% per year)	(1) RN	(2) CP SDF +UMD	(3) HXZ4	(4) Carhart	(5) FF5	(6) RN	(7) CP SDF +UMD	(8) HXZ4	(9) Carhart	(10) FF5	(11) RN	(12) CP SDF +UMD	(13) HXZ4	(14) Carhart	(15) FF5
10-yr	2.35	−0.14	1.89	0.68	1.01	2.35	0.20	1.99	0.78	1.84	2.35	0.08	1.62	1.46	2.20
7-yr	2.55	0.32	2.23	1.26	1.54	2.55	0.59	2.33	1.33	2.25	2.55	0.42	2.03	1.90	2.44
5-yr	2.08	−0.04	1.78	1.09	1.38	2.08	0.07	1.86	1.14	1.86	2.08	−0.22	1.65	1.55	1.87
2-yr	1.32	−0.29	1.08	0.98	0.96	1.32	−0.56	1.12	0.97	1.16	1.32	−1.18	1.06	1.05	1.11
1-yr	1.03	0.01	0.87	0.87	0.85	1.03	−0.26	0.90	0.86	0.93	1.03	−0.76	0.90	0.88	0.87
Market	5.94	−0.71	−0.56	−0.78	−0.04	5.94	−0.93	−0.51	−0.73	−0.44	5.94	−0.95	−0.17	−0.78	−0.35
BM1	5.10	−0.30	0.33	0.56	−0.60	5.10	−0.32	0.28	0.51	−0.37	5.10	−0.28	0.26	0.14	1.86
BM2	6.51	0.26	0.13	0.40	1.19	6.51	0.22	−0.05	0.43	0.39	6.51	0.36	−0.63	0.34	−0.92
BM3	7.20	0.39	0.08	0.11	0.74	7.20	0.05	−0.10	0.15	0.22	7.20	−0.18	−0.81	0.22	−0.75
BM4	6.88	0.15	−0.65	−0.49	−0.45	6.88	0.49	−0.76	−0.51	−0.61	6.88	1.50	−1.31	−0.53	−1.05
BM5	6.39	−0.92	−1.23	−0.32	−1.32	6.39	−0.75	−1.10	−0.51	−0.91	6.39	0.10	−1.32	−0.79	−1.10
BM6	7.63	1.18	−0.13	−1.08	0.11	7.63	1.02	−0.21	−0.94	0.17	7.63	1.11	−0.96	−0.28	−0.69
BM7	7.23	−1.36	−0.99	−0.08	−1.07	7.23	−1.53	−0.67	−0.30	−0.63	7.23	−1.06	−0.29	−0.66	−1.07
BM8	8.07	−0.13	−0.19	−1.01	−0.75	8.07	−0.26	−0.33	−0.93	−0.55	8.07	0.24	−0.40	−0.74	0.74
BM9	10.34	1.36	2.04	1.60	1.07	10.34	1.28	2.00	1.58	1.27	10.34	2.02	2.53	1.36	3.17
BM10	10.59	0.08	0.62	0.61	0.62	10.59	0.31	0.47	0.63	−0.20	10.59	1.99	1.58	−0.01	1.62
S1						8.83	0.90	0.14	0.08	0.53	8.83	0.22	0.47	0.37	−0.71
S2						8.52	−0.02	−0.64	−0.98	−0.53	8.52	−0.82	−0.69	−0.58	−0.80
S3						9.35	0.79	0.31	0.55	0.25	9.35	0.54	−0.03	0.60	0.49
S4						8.52	0.31	−0.20	−0.34	−0.40	8.52	−0.27	−0.89	−0.05	0.48
S5						8.92	0.18	0.41	0.54	0.35	8.92	−0.46	0.12	0.57	0.86
S6						8.19	−0.17	0.20	0.28	0.02	8.19	−0.64	−0.18	0.29	0.94
S7						8.32	−0.22	0.26	0.19	0.53	8.32	−1.07	−0.02	0.35	−0.06
S8						7.70	−0.66	0.11	0.24	0.43	7.70	−0.83	0.42	0.07	−0.44
S9						6.95	−0.37	−0.08	−0.11	0.12	6.95	−0.17	0.10	−0.18	−0.07
S10						5.47	−0.67	−0.12	−0.35	−0.10	5.47	−0.47	0.32	−0.49	0.09
MOM1											0.82	−1.72	−1.49	−2.08	−4.84
MOM2											3.88	−0.54	0.14	0.61	−1.73
MOM3											6.03	1.63	1.27	2.04	0.12
MOM4											6.62	1.54	1.27	1.88	0.52
MOM5											5.92	0.50	−0.06	0.43	−0.06
MOM6											5.78	−0.46	−0.74	−0.45	−0.74
MOM7											6.55	−0.98	−0.48	−0.37	−0.39
MOM8											6.82	−0.69	−0.97	−1.11	−0.49
MOM9											8.25	−0.30	−0.22	−0.75	1.01
MOM10											11.23	0.91	2.59	0.51	4.30
MAPE	5.70	0.48	0.93	0.74	0.86	6.62	0.51	0.66	0.61	0.66	6.50	0.76	0.83	0.74	1.14
Panel B: Prices of Risk Estimates λ_0															
MKT		1.24	4.37	5.69	2.73		1.49	4.16	5.48	2.92		1.98	4.95	4.23	7.01
LVL/SMB/ME		−17.17	−0.12	1.87	−1.58		−16.98	2.43	0.94	2.80		−19.09	5.78	0.66	0.57
CP/HML/IA		23.82	10.50	9.54	15.23		48.70	10.39	8.85	6.78		88.65	13.72	6.13	−14.82
UMD/ROE/RMW		−6.16	0.53	13.21	6.73		−2.43	2.94	11.19	5.16		5.60	11.50	4.55	1.68
CMA					−19.72					−5.51					39.35
Panel C: Test on Risk Prices and Pricing Errors (p-values in %)															
$H_0 : \lambda_0 = 0$		0.24	1.50	3.79	2.16	0.00	1.19	1.74	3.18	2.96	0.00	1.63	0.21	0.07	1.08
H_0 : Pr. error $= 0$		2.42	0.03	0.09	0.33	0.00	6.81	0.05	0.21	0.06	0.00	0.09	0.00	0.00	0.00

It is well known that the 3-factor Fama and French model cannot explain momentum portfolios, and the same is true for our model. We therefore augment both models with a momentum factor (*UMD*). We refer to the extended 3-factor Fama and French model as the Carhart model (Carhart, 1997). In our comparison of factor models, we also consider the recent 4-factor model of Hou et al. (2015) (HXZ4) and the 5-factor model of Fama and French (2015) (FF5).

The second column of Table 4 shows that our model successfully reduces virtually all of the value spread and explains the cross-section of bond returns. The MAPE for this sample is 48 bps. This shows that our main results hold in a more recent sample and for both book-to-market deciles and quintiles. The Carhart and HXZ4 models also eliminate most of the value spread, while the FF5 model leaves 1.2% unexplained. All three models, however, struggle to simultaneously price the cross-sections of stocks and bonds. The MAPE is 93 bps for the HXZ4, 74 bps for the Carhart, and 86 bps for the FF5 model.

If we add size portfolios in columns (6)–(10), then our model reduces the size spreads to 1.6% without sacrificing much of the explanatory ability for the other 16 test assets. The MAPE equals 51 bps. All other models are able to explain the cross-section of size and book-to-market portfolios. Their MAPE are 66 bps for the HXZ4, 61 bps for the Carhart, and 66 bps for the FF5 models. While the MAPE fall for each of these models, the pricing errors of the bond portfolios remain equally large, or increase, for all three alternative models.

In columns (11)–(15) of Table 4, we add the momentum decile portfolios. The momentum spread is large and equal to 10.4% per year. Our model leaves only 2.6% of the momentum premium unexplained, which is the same as for the Carhart model. The HXZ4 model (4.1%) and the FF5 model (9.1%) result in larger pricing errors for the momentum portfolios. The MAPE is lowest for the Carhart model (74 bps), followed by our model (76 bps), the HXZ4 (83 bps), and the FF5 (1.1%) models. The differences for the first three models are small, but, as before, the other models result in larger pricing errors for the bond portfolios than our model.

Table A.V in Appendix B repeats the analysis using investment, size, and return-to-equity deciles instead of the B/M, size, and momentum portfolios. The investment and return-to-equity deciles are from Hou et al. (2015) from January 1967 to December 2015. All models are able to explain the spread in size-sorted portfolios. While our model is able to price the bond portfolios better for any cross-section of test assets that we consider, our model results in larger pricing errors for investment and return-to-equity sorted portfolios compared to the other pricing models. The HXZ4 and FF5 models perform substantially better for the largest cross-section that we consider in Appendix B.

4.2. GMM versus Fama–MacBeth

Much of the cross-sectional asset pricing literature uses the method of Fama and MacBeth (1973). Appendix B.2 finds that are results are nearly unchanged under the Fama–MacBeth methodology. However, it is important to estimate the CP-betas with enough data. Using 60-month rolling-windows leads to imprecise estimates and results in a deterioration of the pricing performance of our model.

5. Model with business cycle risk

The last part of the paper proposes a simple asset pricing model that connects our empirical findings. It formalizes the relationships between the returns on value and growth stocks, the bond risk premium (*CP*), and the state of the macroeconomy. It does so in a pricing framework that quantitatively accounts for the observed risk premia on stock and bond portfolios, the dynamics of dividend growth rates, inflation, and basic properties of the term structure of interest rates. Its role is to clarify the minimal structure necessary to account for the observed moments. In the interest of space, the full model description, solution, and calibration are relegated to Online Appendix F.

The model has one key state variable, s, which is as a leading business cycle indicator. It follows an autoregressive process and its innovations ε^s_{t+1} are the first priced source of risk. Real dividend growth for value (V), growth (G), and market (M) equity portfolios are given by:

$$\Delta d^i_{t+1} = \gamma_{0i} + \gamma_{1i} s_t + \sigma_{di}\varepsilon^d_{t+1} + \sigma_i \varepsilon^i_{t+1}, \ \forall i = \{V, G, M\}.$$

The shock ε^d_{t+1} is an aggregate dividend shock, the second priced source of risk, while ε^i_{t+1} is a 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 shocks in macroeconomic activity than growth stocks. As in the data (Section 2.2.1), a low value for s is associated with lower future dividend growth on V minus G. Our calibration matches the frequency and duration of recessions and chooses γ_{1V} and γ_{1G} to match the decline in dividend growth value minus growth over the course of recessions. Inflation is the sum of a autoregressive process which captures expected inflation and an unexpected inflation shock. Expected inflation, x_t, is the second state variable in the model; its innovation ε^x_{t+1} the third and last priced source of risk. Inflation and dividend growth parameters are chosen to match the unconditional mean and volatility of dividend growth and inflation, as well as the volatility and persistence of one- through five-year nominal bond yields.

Investor preferences are summarized by a real stochastic discount factor (SDF), whose log m 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 constant real rate of interest. The market prices of risk are chosen to match the equity risk premium (the one associated with ε^d), slope of the yield curve (ε^x), and value risk premium (ε^s).

The model generates an affine nominal term structure of log nominal interest rates: $y^\$_t(n) = -\frac{A^\$_n}{n} - \frac{B^\$_n}{n}s_t - \frac{C^\$_n}{n}x_t$. 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.

$$E_t\left[rx^\$_{t+1}(n)\right] = \underbrace{\lambda_0(2)C^\$_{n-1}\sigma_x + \lambda_0(3)B^\$_{n-1}\sigma_s}_{\text{Constant component bond risk premium}} + \underbrace{\lambda_1(2)C^\$_{n-1}\sigma_x s_t}_{\text{Time-varying component bond risk premium}}.$$

Thus, the *CP* factor which measures the bond risk premium is perfectly positively correlated with s_t, the leading indicator of macroeconomic activity. Innovations to the *CP* factor are innovations to s (ε^s), lending a structural interpretation to *CP* shocks

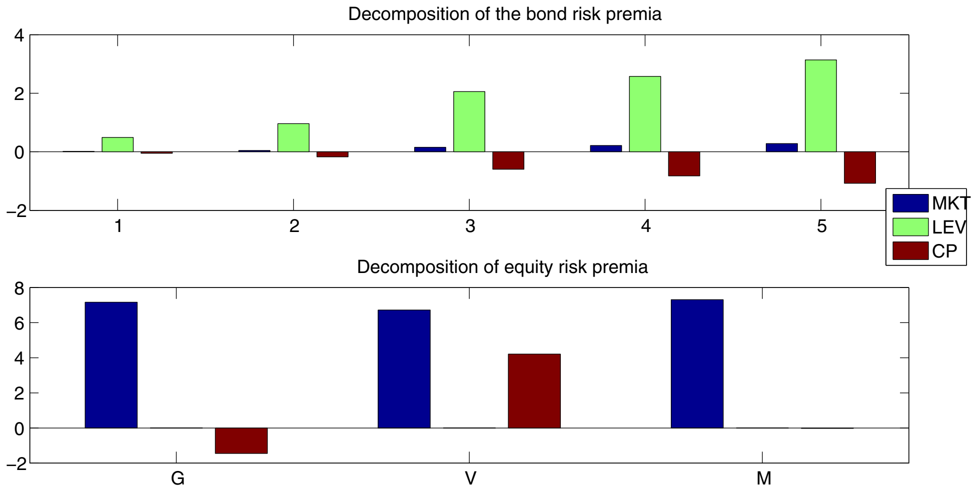

Fig. 6. Decomposition of annualized excess returns in model. The figure plots the risk premium (expected excess return) decomposition into risk compensation for exposure to the *CP* factor, the *LVL* factor, and the *MKT* factor. Risk premia, plotted against the left axis, are expressed in percent per 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 Online Appendix F.3.

which is consistent with our empirical evidence. The constant component of the bond risk premium reflects compensation for exposure to expected inflation risk (first term) and cyclical risk (second term). 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.

Turning to stock pricing, the log price-dividend ratio on stocks is affine in the state s_t: $pd^i_t = A_i + B_i s_t$. The equity risk premium provides compensation for exposure to aggregate dividend growth risk (ε^d) and for cyclical risk (ε^s):

$$E_t\left[rx^i_{t+1}\right] = \underbrace{\lambda_0(1)\sigma_{di} + \lambda_0(3)\kappa_{1i}B_i\sigma_s}_{\text{Constant component equity risk premium}} + \underbrace{\lambda_1(1)\sigma_{di}s_t}_{\text{Time-varying component equity risk premium}}.$$

Shocks to the market return (*MKT*) are a linear combination of ε^d and ε^s shocks. Like bond risk premia, equity risk premia vary over time with the state of the economy s_t. 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: B_i increases in γ_{1i}. Because the price of cyclical risk 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.

For each asset, we can then compute covariances of unexpected returns with the *MKT*, *LVL*, and *CP* shocks, as defined inside the model. Interestingly, we are able to replicate the three-factor risk premium decomposition we uncovered in Section 3. Fig. 6 is the model's counterpart to Fig. 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.[14] The model also generates interesting asset pricing dynamics over the business cycle as detailed in the Online Appendix.

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. *LVL* shocks capture changes in expected inflation. *MKT* shocks mostly capture (permanent) changes in dividend growth. 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.

[14] 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.

6. Conclusion

This paper provides 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. 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. The market price of risk for the latter risk factor is positive, consistent with the notion that positive innovations represent good news about future economic activity.

The 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 in Section 5 is a starting point in this research agenda. More work is needed to help understand why the market compensates exposure to innovations in this state variable so generously.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmoneco.2017.05.006

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