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State Variables, Macroeconomic Activity and the Cross-Section of Individual Stocks

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State variables, macroeconomic activity and the cross-section of individual stocks*

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ABSTRACT

I study whether risk premiums for ICAPM-motivated state variables are consistent with how these variables predict macroeconomic activity. I find that the state variable risk premiums in the cross-section of individual stocks are consistent with investor's incentives to hedge against the systematic economic news that the state variables contain in the time-series. These risk premiums are not fully captured by exposure to the Fama-French-factors nor their underlying characteristics. My findings challenge recent portfolio-level evidence showing that risk premiums are inconsistent with investor's incentives to hedge time-varying consumption-investment opportunities and therefore the ICAPM.

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I link the time-series to the cross-section in the context of asset pricing. I find that risk premiums in the cross-section of individual stocks for exposure to Intertemporal CAPM (ICAPM) motivated state variables are consistent with how these variables predict macroeconomic activity in the time-series. This time-series and cross-sectional consistency alleviates concerns about "factor fishing" and is consistent with the idea that investors desire to hedge against shocks to macroeconomic activity. This finding resuscitates a central role for business cycle risk in asset pricing along the lines suggested by Cochrane (2005, Ch. 9) and Koijen et al. (2013).

The empirical method consists of two elements. First, long-horizons regressions establish whether and how a candidate state variable forecasts macroeconomic activity, as measured by Industrial Production growth or the Chicago FED National Activity Index. Second, to establish whether this state variable is a priced risk factor, I directly identify the individual stocks that are exposed to innovations in the state variable. Following Campbell (1996), these innovations are taken from a $VAR(1)$.[1] I use these exposures to run cross-sectional regressions and sort stocks into portfolios. In this way, I use a broad and heterogenous cross-section of exposures, which is attractive for hedging. Moreover, using individual stocks follows the suggestion that stock-level tests are relatively efficient (Litzenberger and Ramaswamy (1979) and Ang et al. (2011)), whereas inferences from portfolio-level tests depend critically on the chosen set of test portfolios (Ahn et al. (2009) and Lewellen et al. (2010)).

The main contribution of this study is to establish that these two elements are consistent in sign. The sign restriction follows from a stochastic discount factor that prices systematic economic news and therefore exposure to state variables containing this news. This sign restriction is a simple alternative to directly imposing intertemporal restrictions on the risk prices, such as in the $VAR-ICAPM$ of Campbell (1996), to guard against "factor fishing". This concern traditionally undermines tests of the ICAPM (Fama (1991) and Black (1993)). Indeed, existing portfolio-level evidence on the pricing of these state variables is mixed, but

[1] Note, measuring exposures to innovations in the state variables, rather than their levels, separates this work from versions of the Conditional CAPM in Jagannathan and Wang (1996) and Cochrane (1996).

certainly suggestive that pricing is inconsistent with how the state variables predict the aggregate stock market portfolio, which relation is implied by the ICAPM of Merton (1973) (see Maio and Santa-Clara (2012)).[2] However, the aggregate stock market return is likely a poor proxy for the return on aggregate wealth (Roll (1977)), which is the opportunity set of interest to the representative investor. Because investors own human capital, houses, shares of small businesses and other non-marketed assets, besides stocks and bonds, Cochrane (2005, Ch. 9) advocates the search for "recession state variables", i.e., variables that predict macroeconomic activity.

To start out, I focus on the three most commonly used state variables in the literature: Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). I find that DS forecasts negative changes in macroeconomic activity (consistent with Chen (1991) and Gilchrist and Zakrajsek (2012)), TS forecasts positive changes (consistent with Estrella and Hardouvelis (1991) and Adrian and Estrella (2008)), whereas DY is not a robust predictor. Thus, the ICAPM suggests that only exposures to DS and TS risk are priced. Moreover, the ICAPM suggests that the DS risk premium is negative and the TS risk premium positive. Indeed, high DS and low TS exposure stocks pay off when macroeconomic activity is expected to decrease, which makes these stocks attractive as a hedge and lowers their expected returns. Consistent with these predictions, I estimate an annualized average risk premium of -6.5% for DS, 6.0% for TS and around zero for DY in quarterly cross-sectional regressions. The corresponding absolute Sharpe ratio is large at 0.41 and 0.48 for DS and TS, respectively, relative to 0.30 for the market portfolio.

Next, I show that this time-series and cross-sectional consistency is general to the broader set of ICAPM-motivated state variables analyzed in Maio and Santa-Clara (2012). First, I analyze the model of Petkova (2006), which includes the risk-free rate (RF) next to DY, DS and TS.[3] Second, the model of Campbell and Vuolteenaho (2004), which in-

[2] A long history of papers test whether ICAPM-motivated state variables are priced in a set of predetermined portfolios. An incomplete list includes Shanken (1990), Ferson and Harvey (1991), Campbell (1996), Brennan et al. (2004), Petkova (2006), Hahn and Lee (2006) and Kan et al. (2012).

[3] Inspired by Lioui and Poncet (2011), who highlight multicolinearity problems between RF and TS, I consider two versions. First, I substitute RF for TS. Second, I add RF orthogonalized from TS to the original set of state variables. The latter version shows that RF has little to add to a model that already

cludes TS, the price-earnings ratio (PE) and the value spread (VS). Third, the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and a factor that measures the level of the term-structure (LVL). In the long-horizon regressions, RF and VS forecast negative changes in macroeconomic activity, CP forecasts positive changes, whereas PE and LVL are not robust predictors. Consistent with this time-series evidence, I estimate that RF, VS and CP capture an annualized risk premium of -4.0%, -5.5% and +4.5% (an absolute Sharpe ratio of 0.26, 0.38 and 0.33), respectively, whereas PE and LVL risk are not priced.

I find that these conclusions are robust. First, the results are consistent when the time-series and cross-sectional regressions are run at the monthly frequency instead. This finding alleviates concerns about potential horizon-effects in the predictive relations and is important because the investment horizon of the representative agent is unknown (Kothari et al. (1995), Campbell (1996) and Brennan and Zhang (2012)). Also, the results are qualitatively similar when using exposures to first-differences in the state variables instead of $VAR(1)$-innovations.

Finally, the risk premiums are consistent in sign and often in magnitude for value- and equal-weighted High minus Low quintile portfolios. This finding suggests suggests that transaction costs are unlikely to eradicate the risk premiums for the priced state variables (DS, TS, RF, VS and CP) completely. These individual stock-based strategies can be thought of as simple, out-of-sample proxies for the maximum correlation portfolio of Breeden et al. (1989). Because I construct portfolios that are maximally exposed ex ante, an important question is whether the portfolios are exposed ex post. I find that they are, which suggests that the state variables are not useless factors in the sense of Kan and Zhang (1999). Combining, the evidence suggests that these strategies are useful for investors that desire to tilt their equity portfolio towards or away from these intertemporal risks.

I conclude that pricing is consistent with investor's incentives to hedge business cycle risk, which extends Koijen et al. (2013), who focus on the pricing of CP alone. This finding advances an ICAPM literature, starting with Chen et al. (1986) and Ferson and Harvey

includes TS in both the time-series and the cross-section.

(1991), that routinely includes term structure variables as risk factors. In a closely related paper, Maio and Santa-Clara (2012) conclude however that portfolio-level risk premiums for these state variables are inconsistent with hedging incentives in the ICAPM of Merton (1973). Although, Maio and Santa-Clara (2012) estimate risk premiums for DS, RF, VS and CP that are consistent in sign with my estimates, they are largely insignificant. This finding suggests that using individual stocks is indeed more efficient. It is only in case of VS and CP, however, that the sign of the risk premium is consistent with how the level forecasts aggregate stock market returns. Moreover, while TS predicts positive stock market returns as it does macroeconomic activity, the sign of its risk premium is sensitive to the choice of portfolios. Finally, DY, PE and LVL are not priced among portfolios either, but do forecast stock market returns, especially at longer horizons.[4]

This paper also contributes to the debate on whether the Fama and French (1993) factors proxy for intertemporal risk and, as such, to the risk factor versus characteristics controversy discussed in Fama and French (1992), Daniel and Titman (1997) and Chordia et al. (2012). For instance, results in Petkova (2006) and Hahn and Lee (2006) suggest that SMB and HML can substitute for state variables in portfolio-level tests. In contrast, I find that the state variable risk premiums are not driven out by exposures to SMB and HML in stock-level cross-sectional regressions.

However, the DS risk premium is captured by the characteristic Size. This Size effect is consistent with Perez-Quiros and Timmermann (2000) and Baker and Wurgler (2012), who argue that small stocks are more sensitive to business cycle variation in credit conditions. Similarly, the CP risk premium is eradicated by including Size and Book-to-Market. The link between CP exposures and Book-to-Market is studied in more detail in Koijen et al. (2013). These findings are perhaps unsurprising, because characteristics can be measured without error, whereas exposures need to be estimated. Yet, TS, RF and VS are not fully driven out by characteristics, which means that these state variables do contain independent information about the cross-section of expected individual stock returns.

[4] Maio and Santa-Clara (2012) find that risk premiums are similarly inconsistent with how the state variables predict market variance and a measure of market Sharpe ratio.

The rest of this paper is organized as follows. Section I motivates the link between macroeconomic activity and state variable risk premiums in a stochastic discount factor framework. Section II describes the data and methods used. Section III tests for time-series and cross-sectional consistency in the pricing of state variable risk. Section IV analyzes individual stock-based state variable mimicking portfolios. Section V confronts the state variable risk premiums with the Fama and French (1993) factors and characteristics. Section VI summarizes and concludes.

I Motivation

Consider the conditional asset pricing model $E_t(m_{t+1}r_{i,t+1}) = 0$, where $r_{i,t+1}$ is the excess return on asset i and m_{t+1} is the stochastic discount factor (SDF) that exists when the law of one price holds, with the expectation taken given investor's information set at time t. In most equilibrium models, the SDF is a nonlinear function of factors and the model's parameters. Following the standard procedure, I assume that the SDF can be approximated by a constant linear function of factors

$$m_{t+1} = a - b' f_{t+1}, \tag{1}$$

where the factors are the return on the market portfolio as in the CAPM and innovations in a set of K state variables ($\varepsilon_{z,k,t+1} = z_{k,t+1} - E_t(z_{k,t+1})$ for $k = 1, .., K$).[5] Thus, $f_{t+1} = (r_{m,t+1}, \varepsilon'_{z,t+1})'$ and $b = (b_m, b'_z)'$.

In this paper, I test the hypothesis that $b_{z,k} > 0$ when $z_{k,t}$ predicts macroeconomic activity with a positive sign and vice versa. This hypothesis can be motivated by a rational ICAPM, where investors wish to hedge their risk exposure to state variables that contain news about future macroeconomic activity, with good news lowering marginal utility (see Chen et al. (1986), Vassalou (2003), Cochrane (2005, Ch. 9) and Koijen et al. (2013) for similar arguments).

[5] It is straightforward to extend the analysis to allow the SDF-coefficients to vary over time, for instance, as a linear function of instruments (see Cochrane (2005, Ch, 8).

This model is similar to the ICAPM of Merton (1973), where exposure to state variables that predict consumption-investment opportunities are priced in addition to market beta. In his economy, there exist only stocks (and a risk-free asset), such that the opportunity set can be summarized by the first two moments of the aggregate stock market return. The testable implication is that $b_{z,k} > 0$ when $z_{k,t}$ predicts high returns or low volatility or both, in which case marginal utility is low. Using the CRSP value-weighted stock market portfolio, Maio and Santa-Clara (2012) find that for a range of ICAPM-motivated state variables, the estimated risk premiums are generally inconsistent with this logic.

A possible explanation for this inconsistency, which I explore in this paper, follows from Roll's critique (1977) of the CAPM. The aggregate stock return may be poor proxy for the return on the aggregate wealth portfolio, which is the opportunity set of interest to the representative investor. In fact, previous research establishes that state variables, such as the Default Spread (DS) and the Term Spread (TS), predict returns on various components of wealth, which need not all be traded assets (see Cochrane (2005, Ch. 9)). First, both DS and TS predict returns in stock as well as government and corporate bond markets, consistent with their common use as proxies for credit market conditions and the stance of monetary policy, respectively (Keim and Stambaugh (1986) and Fama and French (1989)). In addition, Fama and French (1989) argue that TS captures a term premium that is common to all long maturity assets. Consistent with this argument, Campbell (1996) finds that TS predicts human capital returns. Finally, Hong and Yogo (2012) find that a combination of DS and TS predicts returns in commodity markets, whereas Ang et al. (2013) show that a factor that is common to public and private real estate loads on DS.

A possible solution is to broaden the proxy of the wealth portfolio and include, for instance, non-traded human capital as in Campbell (1996). To sidestep the need to define the exact composition of the wealth portfolio, I follow the advice in Cochrane (Ch. 9) and instead seek "recession state variables", that is, variables forecasting macroeconomic activity.[6] This approach essentially uses macroeconomic growth as a broad proxy for re-

[6] By directly defining the proxy, Campbell (1996) is able to derive intertemporal restrictions on the risk prices. Such restrictions are lost in the general SDF-approach applied here.

turns on the various components of wealth, such that changes in consumption-investment opportunities are described by those state variables that contain news about future growth rates. Fundamentally, this approach assumes that returns on large components of the wealth portfolio are procyclical, which is consistent with extant evidence of a positive correlation between stocks and, for instance, commodities (Hong and Yogo (2012)), human capital (Campbell (1996)) and real estate (Ang et al. (2013)). Moreover, this procyclicality is present in equilibrium asset pricing theory, as noted in Chen (1991) for stocks and bonds. Since financial securities are claims against output, an increase in the productivity of capital positively impacts expected stock returns (see, e.g., Cox et al. (1985)). At the same time, individuals would want to smooth consumption by attempting to borrow against expected future outputs, thereby bidding up long-term interest rates.

Equation (1) implies the following beta asset pricing model:

$$E_t\left(r_{i,t+1}\right) = \lambda_{m,t}\beta_{i,m,t} + \lambda'_{z,t}\delta_{i,z,t}, \tag{2}$$

where $E_t\left(r_{i,t+1}\right)$ is the expected excess return ($r_{i,t+1} = R_{i,t+1} - R_{f,t+1}$) of asset i; the exposures $\beta_{i,m,t}$ and $\delta_{i,z,t}$ are the slope coefficients from the return-generating process $r_{i,t+1} = \alpha_{i,t} + \beta_{i,m,t}r_{m,t+1} + \delta'_{i,z,t}\varepsilon_{z,t+1} + \nu_{i,t+1}$; and, $\lambda_{m,t}$ and $\lambda_{z,t}$ are the market and state variable risk premiums, respectively, all conditional on the information set at time t. The risk premiums are related to the SDF-specification by $\binom{\lambda_{m,t}}{\lambda_{z,t}} = Var_t(f_{t+1})/E_t(m_{t+1})b$, where $E_t(m_{t+1})$ is positive in the absence of arbitrage opportunities. Thus, an additional component in expected return is required and obtained whenever an asset is influenced by systematic economic news, which is consistent with the general conclusion of asset pricing theory (Chen et al. (1986)).

In the following, I analyze the pricing implications from this model using a standard approach, which entails running Fama and MacBeth (1973) cross-sectional regressions of asset returns on historical betas in each period $t+1$ (for more detail, see Section II). To derive testable unconditional implications, note that the periodic risk premium estimates from these regressions equal the return on a zero-investment portfolio that has a beta of one with respect to each respective factor and a beta of zero with respect to the other factors (Fama (1976)). Let us define these risk premiums as $r^{FMB}_{m,t+1}$ and $r^{FMB}_{z,k,t+1}$ for $k = 1,..,K$ in the context of Equation (2). Moreover, going back to Equation (1), define the factors without loss of generality so as to have conditional mean equal to zero ($f^*_{t+1} = f_{t+1} - E_t(f_{t+1})$) and normalize the SDF as $m_{t+1} = 1 - b' f^*_{t+1}$, such that $E_t(m_{t+1}) = 1$.

Combining, we have

$$E_t(r^{FMB}_{m,t+1}) = 1 \times \lambda_{m,t} \text{ and } E_t(r^{FMB}_{z,k,t+1}) = 1 \times \lambda_{z,k,t} \text{ for } k = 1,..,K, \tag{3}$$

which conditions down to

$$E(r^{FMB}_{m,t+1}) = \lambda_m \text{ and } E(r^{FMB}_{z,k,t+1}) = \lambda_{z,k} \text{ for } k = 1,..,K, \tag{4}$$

where $\binom{\lambda_m}{\lambda_z} = E(f^*_{t+1} f^{*\prime}_{t+1})b$ by the law of iterated expectations. Thus, in this paper I estimate the unconditionally expected excess return investors require to invest in a portfolio with a conditional factor beta equal to one.

As pointed out in Fama (1996), the sign of the market risk premium in this ICAPM is indeterminate, because it may hedge against state variable risk. However, when the innovations in the state variables are (close to) orthogonal to the market, which is the relevant case in this paper, λ_m is positive and must equal the expected return on the market portfolio. When the innovations are also (close to) orthogonal to each other, the state variable risk premiums in λ_z are multiples of the respective elements of b_z, such that their signs must be identical. Hence, if a state variable predicts economic activity with a positive sign, an asset that covaries with innovations in this state variable earns a positive risk premium. The intuition is that the asset does not allow the investor to hedge against business cycle risk, such that he will not be willing to pay a high price for this asset.

II Methodology and data

This section describes the data and methods used to test the ICAPM derived above. First, I introduce the long-horizon regressions that determine whether a candidate state variable forecasts macroeconomic activity. Second, I introduce the cross-sectional regression that tests whether exposure to the state variable is priced in a consistent manner.

A Predicting macroeconomic activity

I use two measures of macroeconomic activity: the Industrial Production Index (IP) and the Chicago FED National Activity Index (CF). Both indexes are designed to gauge real output and overall economic activity in the US and are available from the FRED® database of the Federal Reserve Bank of St. Louis. IP is seasonally-adjusted and for both series I use the latest vintage.[7] In this paper, I focus mainly on a quarterly frequency.[8] Throughout, I present select results for the monthly frequency as a check of robustness.

In order to test whether the state variables predict macroeconomic activity, I conduct long-horizon predictive regressions, which are common in the time-series predictability literature:

$$y_{t,t+S} = a_S + b_S' z_t + e_{t,t+S}, \tag{5}$$

where $y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right)$ $(\sum_{s=1}^{S} CF_{t+s})$ measures macroeconomic growth over S periods; z_t is a set of candidate state variables and $e_{t,t+S}$ is a forecasting error with zero mean conditional on z_t. The sign of the slope coefficients in b_S indicates whether a given state variable forecasts positive or negative changes in macroeconomic activity. In the ICAPM of Equation (2), this sign determines the sign of the risk premium for exposure to that state variable in the cross-section. Similarly, Maio and Santa-Clara (2012) conduct these regressions with aggregate stock market returns on the left-hand side to test the ICAPM of Merton (1973). The original sample is 1962.Q1 to 2011.Q4, which corresponds to the time span used in most empirical asset pricing studies of the cross-section.

[7] Results for the real-time vintage series are similar.

[8] Quarterly IP compounds monthly growth rates, whereas quarterly CF is a 3-month moving average.

In the main analysis, z_t includes three popular state variables that are known to predict returns in various asset classes: the Dividend Yield (DY) of the CRSP value-weighted stock portfolio (the ratio of dividends over the last 12 months and the current level of the index), the Default Spread (DS) between the yield of long-term corporate BAA and AAA bonds (both monthly averages) and the Term Spread (TS) between the yield of the ten and one year government bond (both observed at month-end).[9] Data on bond yields are from the FRED® database of the Federal Reserve Bank of St. Louis.

In a number of studies, e.g., Petkova (2006) and Kan et al. (2012), the Risk-Free rate (RF) is included as fourth state variable. I find that RF is largely redundant in the presence of TS and therefore exclude it in the main analysis. The exclusion of RF is attractive also, because it allows me to estimate one beta less per stock, per period. I present results for RF as a robustness check throughout the paper. In this robustness check, I also present results for two competing models. First, the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS).[10] Second, the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and the level factor (LVL).[11]

B Cross-sectional regressions

In order to test the pricing model in Equation (4), I run Fama and MacBeth (1973) cross-sectional regressions of individual stock returns on conditional betas with respect to innovations in the state variables. First, Litzenberger and Ramaswamy (1979) and Ang et al. (2011) argue that stock-level tests may be more efficient than portfolio-level tests, because the wider dispersion in betas, should more than make up for the larger degree of noise in

[9] Gilchrist and Zakrajsek (2012) propose an alternative measure of default risk that is a better predictor of macroeconomic aggregates, based on the cross-section of corporate bond yields. I discuss the pricing of this alternative to DS in a robustness check.

[10] PE is the log ratio of the price of the S&P 500 index to a ten-year moving average of earnings. VS is calculated from six Size and Book-to-market sorted portfolios as in Campbell and Vuolteenaho (2004).

[11] CP is the fitted value from a regression of an average of excess bond returns on forward rates. LVL is the first principal component of the one- through five-year Fama-Bliss forward rates, which is highly correlated to RF (the correlation coefficient equals 0.97 at both frequencies). For details on the construction of both series see Cochrane and Piazzesi (2005).

the estimated betas when estimating risk premiums. Second, conditional exposures ensure that the investor can apply these strategies in real-time and are consistent with extant evidence that stock-level exposures are time-varying. This subsection describes the two main ingredients for these regressions: state variable innovations and betas. Finally, I interpret the cross-sectional regression as a portfolio strategy.

B.1 Innovations

I adopt the approach of Campbell (1996) and assume the state variables follow a first-order Vector Auto-Regressive process ($VAR(1)$).[12] To be consistent with previous work, I use the CRSP value-weighted stock market return as proxy for the market portfolio. To ensure the betas are fully conditional, the VAR uses only historical data in period t. Thus, I estimate $y_\tau = A_0^t + A_1^t y_{\tau-1} + e_\tau^t$, where the superscript t indicates that $\tau = 1, .., t$. Moreover, $y_t = (r_{m,t}, z_t')'$, where z_t collects the state variables, such that $z_t = (DY_t, DS_t, TS_t)'$ in the main analysis. Following Petkova (2006), the innovations e_τ^t are orthogonalized from the market return $r_{m,\tau}^t$ and scaled to have the same variance as $r_{m,\tau}^t$. This orthogonalization is particularly important for DY. When the VAR is estimated over the full sample, the correlation between the excess market return and innovations in DY is -0.89. The innovations are not orthogonalized from each other, because (i) their correlations are below 0.20 and (ii) this could add additional noise through the arbitrary ordering of the variables.[13] The transformed innovations in the state variables, used as risk factors in the asset pricing model in period t, are denoted $\varepsilon_{z,\tau}^t = (\varepsilon_{DY,\tau}^t, \varepsilon_{DS,\tau}^t, \varepsilon_{TS,\tau}^t)'$.

B.2 Betas

I use all ordinary common stocks traded on NYSE, AMEX and NASDAQ (excluding firms with negative book equity). To be consistent with previous work, I exclude financial firms. Although financials are potentially useful for hedging, their inclusion does not meaningfully

[12] The results are qualitatively similar for innovations from a $VAR(2)$, an $AR(1)$ and for first-differences in the state variables. Select results from these robustness checks are discussed below.

[13] Lioui and Poncet (2011) show that results for a VAR-ICAPM are sensitive to the orthogonalization procedure. This sensitivity is particularly strong for RF as is shown in Section III.C.

alter the main conclusions. Furthermore, I require that at least four out of the last five years of returns are available for a stock to be included. I use a weighted least-squares regression over all observations $\tau = 1, ..., t$ and shrink these betas as suggested in Vasicek (1973). These modifications to the usual rolling-window beta are important, because exposures to non-traded factors tend to be small and hard-to-estimate.[14] The expanding window ensures that we use as much information as possible, whereas an exponential decay in the weights ensures timeliness of the estimated betas. Thus, for each stock $i = 1, ..., N_t$ the WLS-estimator of $\delta_{i,t}$ is given by

$$\begin{aligned} \left(\widehat{\alpha_{i,t}}, \widehat{\beta_{i,m,t}}, \widehat{\delta_{i,t}}\right) &= \underset{\alpha_{i,t},\beta_{i,m,t},\delta_{i,t}}{\arg\min} \sum_{\tau=1}^{t} K(\tau) \left(r_{i,\tau} - \alpha_{i,t} - \beta_{i,m,t} r_{m,\tau} - \delta_{i,t}' \varepsilon_{\tau}^{t}\right)^2, \qquad (6) \\ \text{with weights } K(\tau) &= \frac{\exp(-|t-\tau|\ h)}{\sum_{\tau=1}^{t} \exp(-|t-\tau|\ h)}. \end{aligned}$$

With $h = \frac{\log(2)}{20}$ in case of quarterly data (and $h = \frac{\log(2)}{60}$ in case of monthly data), the half-life converges to 5 years for large t. Next, I perform the Bayesian transformation

$$\widehat{\delta_{i,k,t}^{v}} = \widehat{\delta_{i,k,t}} + \frac{var_{TSD}(\widehat{\delta_{i,k,t}})}{\left[var_{TSD}(\widehat{\delta_{i,k,t}}) + var_{CSD}(\widehat{\delta_{i,k,t}})\right]} \left[mean_{CSD}(\widehat{\delta_{i,k,t}}) - \widehat{\delta_{i,k,t}}\right], \qquad (7)$$

where the subscripts TSD and CSD denote means and variances taken over the time-series dimension τ and cross-sectional dimension i, respectively. In this way, $\widehat{\delta_{i,k,t}^{v}}$ is a weighted average of the estimated beta and the cross-sectional average beta, where the former receives a larger weight when it is estimated more precisely. Among others, Elton et al. (1978) and Cosemans et al. (2012) show that this adjustment improves forecasted exposures. For the state variables studied in this paper, the cross-sectional average of the fraction in Equation (7) is about 0.30. Thus, the average amount of shrinkage in this paper is similar to Bloomberg's estimate for market betas. From this point forward, all results are based on these adjusted exposures, simply denoted $\delta_{i,k,t}$. Accounting for a burn-in period

[14] The main results are qualitatively similar, but weaker for the more noisy rolling-window betas.

of five years when estimating beta, the sample period amounts to a total of 179 quarterly (537 monthly) cross-sectional regressions from 1967Q2 to 2011Q4.

B.3 Mimicking portfolio interpretation

In each period t, I estimate risk premiums $\lambda_t = (\lambda_{m,t}, \lambda'_{z,t})'$ by running Fama and MacBeth (1973) cross-sectional regressions for $i = 1, ..., N_t$:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}. \tag{8}$$

As shown in Fama (1976), this cross-sectional regression implicitly defines a strategy that is the purest way to hedge state variable risk, as each element of λ_t can be interpreted as the return on a zero-investment portfolio that has a conditional beta of one with respect to the factor of interest and a conditional beta of zero with respect to all other factors. This result follows from post-multiplying the portfolio weights for state variable k, i.e., the $k+2$-th row of $(B'_tB_t)^{-1}B'_t$ (where B_t has typical row $B_{i,t} = (1, \beta_{i,m,t}, \delta'_{i,t})$), with B_t itself. In the following, I present select for a cross-sectional regression that restricts the intercept to zero ($\lambda_{0,t} = 0$), as dictated by the ICAPM in Equation (2). In this case, the unit exposure portfolio strategy is not restricted to be zero-investment anymore.

Note, because $B_{i,t}$ contains pre-ranking betas, which are noisy, the post-ranking exposure to factor k is likely smaller than one (and to the other factors unequal to zero). To ensure that the state variables are not useless factors in the sense of Kan and Zhang (1999), I test whether the cross-sectional regression portfolios are exposed ex-post to the respective state variable innovation in Section IV.

The cross-sectional regression portfolio can be thought of as simple, out-of-sample proxy of the maximum correlation mimicking portfolio of Breeden et al. (1989). This portfolio cannot be estimated, because there are more stocks than time-series observations. The alternative, using a small set of portfolios as base assets, is unattractive as long as we are uncertain that these portfolios span the cross-section or when these portfolios have a strong factor structure (Lewellen et al. (2010)). For instance, Maio and Santa-Clara (2012) find differences, in both absolute value and sign, between risk premiums estimated using 25 Size and Book-to-Market portfolios and 25 Size and Momentum portfolios.

As a benchmark, I also present results for both market value- and equal-weighted High minus Low spreading portfolios (HLSP) in Section IV, which are split at the quintiles of ranked exposures. These HLSP's are likely more interesting from a practical point of view, because they require an investment in a subset of the available stocks only.

III Time-series and cross-sectional consistency

This section presents the main test of this paper and asks whether the risk premium for exposure to state variable risk in the cross-section of individual stocks is consistent with how this state variable predicts macroeconomic activity in the time-series. First, I present both time-series and cross-sectional regressions for the three most popular state variables in the empirical asset pricing literature, that is, the Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). Subsequently, I ask whether the main conclusions from this exercise are general to a broader set of ICAPM-motivated state variables.

A Do state variables predict macroeconomic activity?

Time-series predictability is a necessary condition for a state variable to be priced in the ICAPM of Equation (2). When there are multiple state variables, we should focus on the marginal predictive role of each variable, conditional on all other variables. For this reason, Table I presents both single and multiple regressions of current and future Industrial Production Growth (IP) or Chicago Fed National Activity Index (CF) on the state variables, where all variables are standardized to accomodate interpretation.[15] I use as forecasting horizon $S = 0$, 1, 2, 4, 8 and 20 quarters in Panel A and $S = 0$, 1, 6, 12, 24 and 60 months in Panel B. I use both Newey and West (1987) and Hansen and Hodrick (1980) asymptotic standard errors with S lags to correct for the serial correlation in the residuals induced by

[15] R^2 is not reported for the single regressions, because it is equal to the square of the estimated regression coefficient.

the overlapping data.

Let us initially focus on the single regressions for IP at the quarterly frequency. First, DY predicts current and next quarter IP with a marginally negative coefficient that translates to an R^2 of about 3%, but does not predict at longer horizons. Similarly, DS predicts current and short-term future IP with a negative sign. The coefficient is significant up to two quarters ahead and translates to an R^2 that falls from 20% for $S = 0$ to 6% for $S = 2$. In contrast, TS predicts short- and long-term future IP with a positive sign. The coefficient is significant up to eight quarters out and translates to an R^2 increasing from 3% for $S = 1$ to 13% for $S = 8$. In unreported results, I find that the TS coefficient is positive and significant up to $S = 18$, but peaks around $S = 8$.

In multiple predictive regressions, the three variables jointly explain about 15% to 20% of the variation in both short- and long-term future IP. The coefficients for DS and TS are consistent in sign with, but strenghten relative to the single regressions. DS is the most important predictor of current and short-term future IP, with a negative coefficient that remains significant up to $S = 8$. TS is the most important predictor of long-term future IP, with a positive coefficient that is significant up to $S = 20$. In the presence of DS and TS, DY turns out to be a positive predictor of long-term future IP, in contrast to the single regression. The DY coefficient for $S > 8$ is economically large above 0.30, but typically insignificant, however. In the remaining blocks of Panel A, we see that these results are robust for CF. Moreover, Panel B demonstrates that these conclusions largely extend at the monthly frequency.

In terms of the model, these predictive regressions clearly indicate what the sign of the risk premium for exposure to DS and TS must be. DS predicts short-term future economic activity with a negative sign, consistent with evidence in Chen (1991) and Gilchrist and Zakrajsek (2012). In contrast, TS predicts (long-term future) economic activity with a positive sign. In fact, a negative TS has preceded all US recessions since the 50s, with only one false signal (see, e.g., Adrian and Estrella (2008)). Thus, it is natural to interpret an increasing DS as bad news and an increasing TS as good news, such that their risk premiums must be negative and positive, respectively.[16]

In contrast, the regressions do not allow for a clear-cut interpretation of an increasing DY as either good or bad news. On one hand, DY predicts positive changes in long-term future macroeconomic activity in multiple regressions, which suggests the risk premium must be positive. On the other hand, these positive long-term coefficients are (i) poorly estimated, (ii) insignificant in single regressions, where the short-term coefficients are actually marginally significant with the opposite sign, and (iii) sensitive to the chosen sample period. For instance, DY predicts current and short-term future macroeconomic activity with a marginally negative coefficient pre-1990 in multiple regressions, consistent with Chen (1991).[17]

Finally, note that DY, DS and TS all predict positive stock market returns in Maio and Santa-Clara (2012), such that the ICAPM of Merton (1973) implies that all three risk premiums are positive. Next, I estimate risk premiums in the cross-section of individual stocks to evaluate these two competing sets of predictions.

B Is exposure to state variable risk priced?

Table II presents results for the Fama and MacBeth (1973) stock-level cross-sectional regressions of Equation (8). For the periodically estimated risk premiums $\lambda_t = (\lambda_{m,t}, \lambda'_{z,t})'$, I present the annualized unconditional average: $\widehat{\lambda} = \frac{1}{T}\sum_t \widehat{\lambda}_t$, which is my estimate of the state variable risk premium, as well as the Fama and MacBeth (1973) t-statistic, which uses the time-series standard deviation of the estimate. Also, I present the average cross-sectional $R^2 = \frac{1}{T}\sum_t R^2_t$. Consistent with the long-horizon regressions in Table I, I consider a two-factor model that includes DY, DS or TS next to MKT as well as a joint four-factor

[16] In unreported results, I run predictive regressions for realized variance in stock and bond markets as well as consumption. The results are very much consistent with the interpretation of an increasing DS as bad news, because it predicts realized variance with a positive sign and consumption with a negative sign, and an increasing TS as good news, because it predicts realized variance with a negative sign and consumption with a positive sign. In fact, in absolute magnitude the coefficients for consumption and IP are similar.

[17] The results for DS and TS are qualitatively similar pre- and post-1990. These results are available upon request.

model.

Let us initially focus on the quarterly regressions in Panel A. In the two-factor models, only the DS risk premium is significant at -8.15% ($t = -3.24$). The TS risk premium is non-negligible economically at 2.85%, but insignificant ($t = 1.34$), whereas the DY risk premium is essentially zero. In the four-factor model, which is most relevant in the presence of multiple state variables, the risk premium for DS and TS are large and significant at -6.50% ($t = 2.75$) and 5.77% ($t = 3.20$), respectively. In both cases, this risk premium is consistent with the predictive regressions of Table I and the consequent interpretation of an increasing DS as bad news and an increasing TS as good news. Again, the DY risk premium is small and insignificant, which is consistent with the absence of a robust relation between DY and macroeconomic activity.

In the joint model, the average cross-sectional R^2 equals 3.71%, which is typical for this exercise (see, e.g., Fama and French (2008)). Throughout, the MKT risk premium is positive, but small and insignificant at about 2%. When we restrict the intercept to zero, the MKT risk premium changes dramatically to a large and significant 7%. This result is common in the literature. When the intercept is restricted to zero, MKT beta is used to fit the equal weighted average return of the tests assets in the cross-sectional regression, because this beta is centered around one. This estimate is close to the sample average return on the MKT portfolio and implies an economically plausible relative risk aversion coefficient of about 2 in the ICAPM of Merton (1973) and Campbell (1996).[18] Moreover, when we restrict the intercept to zero, the TS risk premium is larger by about 1% and as a result marginally significant in the two-factor model at 3.74% ($t = 1.72$).

The estimates are quantitatively similar at the monthly frequency in Panel B. For instance, in the four-factor model, the risk premiums for DS and TS are large and significant at -5.28% ($t = -2.21$) and 5.49% ($t = 2.69$), respectively, whereas the risk premium for DY remains insignificant at 1.54%. Moreover, these results are qualitatively robust in Panel C,

[18]To be precise, because the state variable innovations are orthogonalized from MKT, the estimated relative risk aversion coefficient is the ratio of the estimated MKT risk premium and the variance of the MKT portfolio, that is, $\frac{0.07/4}{0.09^2} = 2.16$.

where we estimate exposures with respect to first-differences in the state variables instead of $VAR(1)$-innovations.[19] Quantitatively, two differences stand out, however. First, the risk premium for TS is smaller by about 2%, but typically remains significant. Second, the DY risk premium turns negative and significant when excluding the intercept. The latter result is solely due to the fact that simple changes in DY are strongly correlated with the MKT return, which is why I have orthogonalized the $VAR(1)$-innovations from the MKT as in Campbell (1996).

To sum up, I estimate risk premiums for DY, DS and TS in the cross-section of individual stocks that are largely consistent with the ICAPM derived in Section I. DS and TS are robust predictors of macroeconomic activity and their respective risk premiums are large and significant around -6% and +6%, respectively.[20] Throughout the DY risk premium is positive, but insignificant, which is consistent with how DY predicts macroeconomic activity. On one hand, DY predicts long-term future activity with a positive sign in multiple regressions. On the other hand, this relation is poorly estimated and not robust across specifications and sample periods. In fact, when I split the sample in two, the average DY risk premium equals -1.79% pre-1990 and 4.24% post-1990. This increase is consistent with the finding that DY predicts negative changes in macroeconomic activity in multiple regressions pre-1990, but positive changes over the full sample.

These stock-level risk premium estimates compare to previous portfolio-level estimates as follows. First, the DS risk premium is also negative among portfolios, but insignificant, which suggests this risk premium is indeed estimated more efficiently using individual stocks. Second, the estimated DY risk premium is typically negative and insignificant among portfolios. As Maio and Santa-Clara (2012) note, the sign of the portfolio-level estimate is inconsistent with the ICAPM of Merton (1973), because both DS and DY

[19] Further, the Internet Appendix demonstrates that the results are both qualitatively and quantitatively similar for $VAR(2)$-innovations in the state variables.

[20] The Internet Appendix demonstrates that the alternative measure of default risk in Gilchrist and Zakrajsek (2012) is priced similar to DS with a quarterly risk premium of -5.89% relative to -5.83% for DS over the period 1978.Q2 to 2010.Q3, which is dicated by data availability. Moreover, the correlation over time between the two risk premiums is 0.75. This finding suggests that DS contains a large chunk of the information relevant for pricing in the alternative measure.

predict positive stock market returns. Third, Maio and Santa-Clara (2012) find that the sign of the TS risk premium is sensitive to the choice of portfolios. A positive TS risk premium is consistent with both versions of the ICAPM, however, as TS predicts both positive stock market returns and macroeconomic activity.

C Alternative ICAPM-motivated state variables

Having established that the time-series is consistent with the cross-section in case of DY, DS and TS, this subsection asks whether this consistency is general to a broader set of ICAPM-motivated state variables. For this exercise, I focus on four alternative models inspired by Maio and Santa-Clara (2012) as described in Section II. First, I analyze a three-factor model that replaces TS with RF, the 3 month t-bill rate. Second, I include RF next to DY, DS and TS. Here, I first orthogonalize RF from TS (denoted RF|TS), to alleviate multicollinearity concerns due to a high correlation between the levels of these variables: -0.62, but even more so their (full sample) $VAR(1)$-innovations: -0.82. Third, I consider the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS). Finally, I analyze the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and a term structure level factor (LVL).

C.1 Time-series

Table III presents the time-series regressions of IP and CF on the alternative state variables, similar to Table I. For this exercise, I focus solely on the quarterly frequency, because results at the monthly frequency are largely similar.[21] Moreover, I focus solely on the coefficients for the new state variables, because the evidence for DY, DS and TS is largely unchanged from Table I. In this table, ***, ** and * indicate significance at the 10%, 5% and 1%-level, respectively, using the more conservative Hansen and Hodrick (1980) asymptotic standard errors with S lags. To conserve space, I report results only for multiple regressions and

[21] These results are presented in the Internet Appendix.

three horizons $S = 1, 4, 8$.

In Model (1), RF predicts four and eight quarter ahead IP and CF with a significant negative coefficient. In unreported results, I find that this predictability is significant from $S = 3$ to $S = 24$, and peaks at $S = 8$. This pattern is similar to TS and consistent with evidence in Chen (1991) and Estrella and Hardouvelis (1991), among others. These authors argue that higher real rates today imply low current investment opportunities and lower output in the future. Thus, I predict a negative risk premium for exposure to RF, because high RF exposure stocks are attractive as a hedge.

Also, consistent with Chen (1991) and Estrella and Hardouvelis (1991), RF does not contain much independent information about future macroeconomic activity relative to TS. In Model (2), the magnitude of the negative coefficient for RF|TS is about half what it is in Model (1) for $S = 4$ and 8. In case of CF, these coefficients are practically zero. Thus, I conclude that the risk premium for RF|TS should be zero.

In Model (3), VS predicts next-quarter IP with a negative coefficient that is significant at the 5%-level. VS is more important in predicting CF, with a negative coefficient that is significant at the 1%-level for $S = 1$ and 4. In fact, in unreported results I find that VS predicts future CF with a negative and significant coefficient up to $S = 7$. This predictability is consistent with Campbell and Vuolteenaho (2004), who find that shocks to VS are an important component of market cash flow news, with a negative correlation between the two. Indeed, if a positive shock to VS predicts lower macroeconomic activity, one would expect market cash flows (dividends) to fall. In contrast, PE only predicts one quarter ahead IP with a marginally positive coefficient, whereas this variable is insignificant at all three horizons in case of CF. In single regressions, PE is also largely insignificant, whereas VS remains an important negative predictor of CF, in particular. Consequently, the risk premium for exposure to VS should be negative, whereas exposure to PE risk should not be priced.

In Model (4), CP predicts predicts eight quarter ahead macroeconomic activity with a positive coefficient that is significant at the 1%-level, consistent with Koijen et al. (2013). For both IP and CF, this predictability is (marginally) significant from about one to five years into the future, with a peak around three years. The coefficient for the LVL factor is negative at all three horizons and for both IP and CF, which is consistent with RF. However, there is likely not enough information for an investor to use this variable to hedge against time-varying investment opportunities, because it is only marginally significant at $S = 8$ in case of IP. Consequently, I predict a positive risk premium for CP, whereas exposure to LVL risk should not be priced.

C.2 Cross-section

Table IV presents stock-level Fama and MacBeth (1973) cross-sectional regressions for the alternative sets of state variables (with conditional betas estimated as in Equations (6) and (7)). The structure is similar Table II and I present unconditional average annualized risk premiums, the corresponding Fama and MacBeth (1973) t-statistics (in parentheses), and the average cross-sectional R^2.

In Model (1), the risk premium for RF is negative, as predicted, at a marginally significant -3.64% ($t = -1.77$). The inclusion of RF instead of TS has little effect on the risk premiums for DY and DS. A negative RF risk premium is consistent in sign with previous portfolio-level evidence with one caveat: RF has little to add to a model that already includes TS. Indeed, in Model (2), RF|TS is insignificant at 1.43%, consistent with the fact that RF|TS does not predict macroeconomic activity in the presence of TS.[22]

In Model (3), the risk premium for exposure to innovations in PE is insignificant at 1.67%, as hypothesized. In contrast, exposure to VS is priced at an economically large and significant -5.23 ($t = -2.56$). These findings are consistent with evidence in Campbell and Vuolteenaho (2004) in that shocks to VS (PE) are an important negative component of market cash flow news (market discount rate news), whereas the risk premium for exposure to market cash flow news is large relative to the risk premium for exposure to market discount rate news. In model (4), exposure to CP is priced at 4.21% ($t = 2.23$), which is

[22] The reverse is not true: TS|RF remains significant in the cross-sectional regression when RF is included already. The same result obtains for 25 Size and Book-to-Market portfolios. These results are available upon request.

consistent with the finding that CP predicts macroeconomic activity with a positive sign as in Koijen et al. (2013). In contrast to these authors, but consistent with the lack of a robust relation between LVL and future macroeconomic activity, I find that LVL is insignificant at 2.35%.[23]

These results are robust to restricting the intercept to zero. In this case, the MKT risk premium is again forced up to about 7%, whereas the risk premiums for RF, VS and CP are slightly larger in absolute value. Moreover, the results are largely similar at the monthly frequency. The main difference is that the risk premiums for VS and CP increase considerably to -8.63% ($t = -3.44$) and 5.85% ($t = 2.64$), respectively. Also, the Internet Appendix presents similar pricing evidence when exposure is measured with respect to first-differences or $VAR(2)$-innovations in the alternative state variables.

To sum up, I find that the risk premiums for innovations in the set of alternative state variables RF, PE, VS, CP and LVL are also consistent with whether or not their level is a robust predictor of macroeconomic activity in the time-series and, when it is, with the sign of the predictive relation. This result compares to Maio and Santa-Clara (2012) as follows. In case of RF, VS and CP the estimated risk premium has the same sign among portfolios, but is insignificant, which again suggests that using individual stocks is more efficient. In case of VS and CP, the sign is consistent with how each variables predicts stock market returns and therefore the ICAPM of Merton (1973). In contrast, the risk premium for RF is negative, whereas this variable predict positive market returns. Finally, the risk premiums for PE and LVL are similarly insignificant among portfolios, and as argued in Maio and Santa-Clara (2012), this finding is inconsistent with the fact that these variables do predict stock market returns.

[23]Because LVL and RF are highly correlated, I add LVL to DY and DS in a robustness check. In this setup, the LVL risk premium turns negative, but remains small and insignificant. These results are available upon request.

IV Individual stock-based state variable mimicking portfolios

This subsection presents the portfolios implicit in the cross-sectional regression procedure in more detail. As a benchmark, I present results for market value-weighted and equal-weighted portfolios split at the quintiles of ranked values. First, I test whether each portfolio is exposed to the risk factor it is supposed to mimick ex post, which is a prerequisite for the portfolios to capture a risk premium and ascertains that the state variables are not useless factors in the sense of Kan and Zhang (1999). Next, I analyze whether the portfolios (i) load on stocks with certain characteristics and (ii) are costly to trade. Throughout, I focus on the quarterly frequency, because these portfolios mimick better, whereas quarterly rebalancing reduces transaction costs.[24] As before, I focus first on DY, DS and TS. Subsequently, I present outtakes of largely consistent results for the alternative state variables.

A Dividend Yield, Default Spread and Term Spread

Panel A of Table V presents post-ranking exposures $(\beta_m, \delta')'$ from the four-factor model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t})' + u_t$ as well as the weighted cross-sectional average pre-ranking exposure within a portfolio. The innovations ε^{Full}_t are estimated with a single $VAR(1)$, where the residuals are orthogonalized from $r_{m,t}$ and scaled to have the same variance as $r_{m,t}$. For each state variable k, I present exposures for three mimicking portfolios: the cross-sectional regression portfolio (FMB) as well as a market value-weighted and an equal-weighted spreading portfolio ($HLMV$ and $HLEW$).[25]

In short, all strategies create a mimicking portfolio that is exposed to the relevant risk factor ex post. The typical mimicking portfolio is only exposed to the one state variable that it is trying to mimick. Moreover, we see a roughly monotonic pattern moving from High to Low among the long-only market-value weighted portfolios. The loadings are typically

[24] Select results at the monthly frequency are described below. The complete set of results can be found in the Internet Appendix.

[25] I do not present results for the cross-sectional regression portfolio where the regression restricts the intercept to zero, because this portfolio is not zero-investment.

significant and smallest for $HLEW$ at about 0.10 and largest for FMB at 0.29, 0.32 and 0.17 in case of DY, DS and TS, respectively. The relative success of FMB in creating an ex post exposure could be due to the fact that it can exploit cross-sectional correlation between exposures to the factors that is stable over time. The difference between ex post exposures and ex ante exposures, which are about one for all strategies, is due to imperfect prediction of the betas. This finding is common in out-of-sample exercises with non-traded factors. Nevertheless, the ex-post exposures are economically meaningful, translating to incremental quarterly returns ranging from 1.5% to 2.8% in case of FMB for a standard deviation increase in the risk factors. Thus, I conclude that these state variables are not useless factors.

The remaining columns of Panel A present annualized unconditional average return, standard deviation and Sharpe ratio. First, the average returns for $HLMV(DY)$ and $HLEW(DY)$ are similarly small and insignificant as $FMB(DY)$, suggesting again that DY risk is not priced. In contrast, DS risk is rewarded with a consistent negative premium. In case of $HLEW(DS)$, the risk premium is slightly smaller than, but similarly significant as $FMB(DS)$ at -4.59% ($t = -2.37$) versus -6.56% ($t = -2.75$). The absolute Sharpe ratio for these two strategies is large relative to the aggregate stock market at 0.35 and 0.41 relative to 0.30. The risk premium is insignificant in case of $HLMV(DS)$, however, which is suggestive of a Size effect. Finally, TS risk is rewarded with a consistent positive risk premium. The risk premiums are large and significant in all weighting schemes at over 4.90% per annum, which translates to Sharpe ratios ranging from 0.34 for $HLMV(TS)$ to 0.54 for $HLEW(TS)$.

At the monthly frequency, these results are largely similar for DY and TS, in which case the post-ranking exposures are only slightly smaller. In case of DS, the post-ranking exposures are positive, but insignificant, however. The presence of a Size effect is even more evident at this frequency, given large and significant negative DS risk premiums for $HLEW(DS)$ and $FMB(DS)$, but an insignificant positive risk premium for $HLMV(DS)$. This variability is perhaps unsurprising given that these portfolios are not strongly exposed ex post to DS risk in the first place.

Panel B of Table V describes the DY, DS and TS mimicking portfolios in terms of various characteristics. In each period, Size ($ billion), Book-to-Market and Momentum are weighted cross-sectional averages, whereas HH is a Herfindahl-index that sums squared portfolio weights ($\sum_i w_{i,t}^2$) and Turnover (annualized) is the amount of trading required to rebalance.[26] For $HLMV$ and $HLEW$, Turnover is calculated as

$$\frac{\sum_i \left| w_{i,t-1} \left(\frac{1}{2} \sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right| \right) - w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}{\sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}. \tag{9}$$

The numerator sums all absolute changes in the portfolio weights from the instant before rebalancing to the instant after, where the latter is scaled to ensure that the long and short position grow equally over time. The denominator scales by the size of the portfolio. For FMB, the total long and short position do not equal one dollar and vary over time. To ensure that trading keeps the pre-ranking beta equal to one, Turnover is calculated as

$$\frac{\sum_i \left| w_{i,t-1} - w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}{\sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}. \tag{10}$$

To start, note that none of the strategies consistently loads on winners or losers and let us focus on $HLEW$, because this weighting scheme presents results that are typical and most comparable to previous work.[27] First, high DY exposure stocks are smaller and have marginally higher Book-to-Market ratios. Second, Size and Book-to-Market are also significant for DS mimicking portfolios at 0.91$ billion and -0.36, respectively. This Size effect is consistent with Perez-Quiros and Timmermann (2000), who argue that small firms are more vulnerable to variation in credit market conditions over the business cycle, such

[26]Book-to-Market (BM) is calculated in June as the ratio of the most recently available book-value of equity in Compustat (assumed to be available six months after the fiscal year-end) divided by Market Capitalization from CRSP (Size) at previous year-end. Momentum is defined as $\prod_{j=4}^{1} \left(1 + r_{i,t-j}\right)$ and $\prod_{j=12}^{2} \left(1 + r_{i,t-j}\right)$ at the quarterly and monthly frequency, respectively.

[27]Note, Size is extreme in case of $HLMV$, because this strategy implicity squares market values.

that an increasing DS signals higher discount rates for smaller stocks. Since low DS beta stocks are also volatile, one can consider them "speculative" in the sense of Baker and Wurgler (2012). Similarly, because high Book-to-Market is indicative of relative distress (Fama and French (1995)), a negative relation with DS risk is natural. Third, high TS exposure stocks are smaller by 1.29$ billion, whereas their Book-to-Market ratio is higher by 0.17. Both characteristics are consistent with Petkova (2006) and Hahn and Lee (2006). A possible explanation is that small firms are marginal firms and therefore more sensitive to news about the business cycle (Chan and Chen (1991)). Further, Cornell (1999), Campbell and Vuolteenaho (2004) and Da (2009), among others, argue that value stocks are low duration assets, such that when an increasing TS signals higher discount rates on long-term assets, value will outperform growth contemporaneously.

In unreported results, I find that Book-to-Market is monotonically related to pre-ranking exposures to DY, DS and TS. In contrast, Size presents an inverted U-shape, because small stocks have more extreme betas. I conclude that if the characteristics Size and Book-to-Market explain the cross-section of expected returns completely, one would expect an unconditional risk premium that is positive for DY and TS, but negative for DS. In Section V, I test whether these benchmark characteristics are able to capture the risk premiums for DS and TS consistent with this hypothesis.

In terms of transaction costs, the $HLMV$ portfolio is likely most attractive. This portfolio invests only in a subset of the available stocks, whereas larger stocks are more liquid. Also, the Herfindahl-index suggests that this portfolio is most concentraded. In terms of concentration, FMB is similar to $HLEW$, which suggest that the former is not requiring an investor to take extreme positions. Rather, FMB requires the investor to take many small positions. Nevertheless, transaction costs are unlikely to completely wipe out the average returns for either of these strategies. In particular, I find that average annual Turnover is about 1.6 for all strategies. This figure implies that an investor who is long and short one dollar and rebalances quarterly, will trade 3.2 dollars per year.[28] Assuming a conservative

[28]Rebalancing the portfolios monthly increases the amount of trading by about 30%. Rebalancing the portfolios only at the end of the year rougly halves the amount of trading required and leaves all other

average quoted half-spread of 25 basis points, these trades add up to transaction costs of about 80 basis points (see, e.g., Chordia et al. (2011) and Hendershott et al. (2011)). As a benchmark, I calculate the amount of trading required to construct comparable portfolios for exposures to SMB and HML as well as for the characteristics Size and Book-to-Market. For these strategies, transaction costs are lower, but only by about 30%. On the other hand, for comparable Momentum strategies, the required amount of trading is larger by over 100%.

B Alternative ICAPM-motivated state variables

This subsection compares the unconditional performance of the three mimicking portfolios ($FMB, HLMV$ and $HLEW$) for the alternative state variables and asks whether these portfolios are exposed ex post. To conserve space, Table VI presents results only for the quarterly frequency and excludes the second model with DY, DS, TS and RF|TS.[29] Moreover, I do not analyze the mimicking portfolios for DY, DS and TS here, because these results are largely similar to Table V.

First, the risk premiums for RF, VS and CP are consistent in sign over the three strategies. In case of RF, the three risk premiums are significant and range from -6.34% for $HLEW(RF)$ to -3.64 for $FMB(RF)$. In case of VS and CP, there is more variation in absolute magnitude, which is suggestive of a Size effect that is further explored in Section V. The risk premiums are insignificant in case of $HLMV$, but significant otherwise at -3.79% (-5.23%) and 2.98% (4.21%), respectively, in case of $HLEW$ (FMB). Second, average returns are small and insignificant across the board for mimicking portfolios of innovations in PE and LVL.

To sum up, I find that the cross-sectional risk premiums for the alternative factors are robust in portfolio sorts. In case of RF, VS and CP, the various strategies typically obtain Sharpe ratios that are in the same order of magnitude as the aggregate stock market. Moreover, in unreported results, I find that the required amount of trading to execute these

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results largely unchanged.

[29] Results at the monthly frequency can be found in the Internet Appendix.

strategies is similar to DS and TS, such that transaction costs are unlikely to eradicate these average returns completely. These conclusions come with the caveat that the post-ranking exposure of these mimicking portfolios to the relevant factor is not always significant at the quarterly frequency. The exposures are consistently positive, however. Moreover, in the Internet Appendix, I show that post-ranking exposures are typically larger at the monthly frequency, whereas the risk premiums are largely similar.[30]

In unreported results, I find that these portfolios load distinctively on the characteristics Size and Book-to-Market, which is similar to DS and TS. To be precise, RF (VS and CP) portfolios demonstrate a large cap (small cap) tilt, whereas RF and VS (CP) portfolios demonstrate a Growth (Value) tilt. To analyze whether the state variables contain independent information for the cross-section of expected returns, the next section includes these characteristics (and the factors SMB and HML derived from them) in cross-sectional regressions.

V Relation to the Fama and French (1993) factors

This section analyzes how the state variable risk premiums relate to both the Fama and French (1993) factors (SMB and HML) and their underlying characteristics (Size and Book-to-Market). In this way, I respond to (i) Fama and French (1993, 1996), who appeal to the ICAPM for theoretical justification, (ii) Petkova (2006) and Hahn and Lee (2006), who argue that innovations in similar sets of state variables may substitute for SMB and HML, and (iii) the risk factor versus characteristic controversy discussed in Fama and French (1992), Daniel and Titman (1997) and Chordia et al. (2012), among others.

[30] Koijen et al. (2013) perform a sort on rolling 60-month covariances with CP innovations in five market-value weighted groups. The high minus low return spread is 2.5%, but its t-statistic is not reported. In the monthly sort reported in the Internet Appendix, I find a similar risk premium of 3.08%.

A Dividend Yield, Default Spread and Term Spread

To start, Panel A of Table VII presents time-series regressions of the Fama and MacBeth (1973) cross-sectional regression risk premiums on the Fama and French (1993) three-factor model (FF3M) as well as the Carhart (1997) four-factor model (FFCM). Results are similar at the quarterly and monthly frequency, so let us focus on the former.

First, the portfolios $FMB(DY)$, $FMB(DS)$ and $FMB(TS)$ are exposed to SMB and HML in a manner that is largely consistent with the characteristics of Table V. In case of TS, a large and significant loading on HML captures its risk premium only partially, leaving an economically large and significant FF3M α of 4.20%, down from 5.79%. In contrast, a large part of the negative DS risk premium is captured by negative loadings on SMB, in particular, and HML, leaving an insignificant FF3M α of -2.89%, up from -6.50%. Adding MOM increases the α slightly for TS, but dramatically for DS, to an economically large, although insignificant FFCM α of -5.26%. In both the FF3M and FFCM, the DY risk premium remains small and insignificant.

In all, these time-series regressions suggest that the DS risk premium is a compensation for exposure to SMB and HML, whereas the TS risk premium is not. This suggestion does not mean, however, that exposures to DS and TS do not contain independent information about average returns in the cross-section. To answer this question, we must perform high-dimensional portfolio sorts or cross-sectional regressions. I follow the advice in Cochrane (2011) and run stock-level cross-sectional regressions, where the set of independent variables includes (i) conditional exposures to $VAR(1)$-innovations in the state variables DY, DS and TS, (ii) conditional exposures to the benchmark factors (MKT, SMB, HML and MOM), and (iii) characteristics (Size, Book-to-Market and Prior return).[31]

Using the procedure set out in equations (6) and (7), I start out regressing returns in each expanding window on an extended factor model that includes the benchmark factors

[31] Following Chordia et al. (2012), Size is the natural logarithm of Market Capitalization and Book-to-Market (BM) is the natural logarithm of the Book-to-Market ratio winsorized at the 0.5th fractile. All characteristics are standardized cross-sectionally.

SMB and HML. Then, in each period t, I estimate

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda_{s,t}\widehat{\beta_{i,smb,t}} + \lambda_{h,t}\widehat{\beta_{i,hml,t}} + \lambda'_{c,t}(Size_{i,t}, BM_{i,t})' + \upsilon_{i,t}. \tag{11}$$

First, I restrict $\lambda'_{z,t} = \lambda'_{c,t} = 0$ to answer the question whether the benchmark factors SMB and HML are priced in the cross-section of individual stocks. Second, I restrict $\lambda'_{c,t} = 0$ to test whether exposures to DS and TS contain information about average returns that is orthogonal from SMB and HML. Third, I restrict $\lambda_{s,t} = \lambda_{h,t} = 0$ to test whether the state variable risk premiums are robust to the inclusion of characteristics, which is a simple test of model misspecification (Berk (1995) and Jagannathan and Wang (1998)). Note, however, that this test is biased in favor of characteristics, because these are measured without error.[32] Fourth, I estimate the full model in Equation (11). Finally, I estimate an extended model that includes both the momentum factor (MOM) and characteristic (Prior return). Throughout, I also present results for a model that restricts $\lambda_{0,t} = 0$.

Let us first consider the quarterly frequency in Panel B. In the FF3M, the risk premiums for SMB and HML are positive at 1.91% and 2.63%, respectively. Even though HML is significant at the 5%-level, this estimate is small relative to the factor's average return of 5%. The FF3M explains a similar amount of cross-sectional variation as the ICAPM-model in Table II at an R^2 of 4.24%. In fact, adding SMB and HML to this model has only a minor effect on the risk premiums for DS and TS, which remain large and significant at -5.58% (t = 2.52) and 4.20% (t = 2.61), respectively. Conversely, the risk premiums for SMB and HML do not change much relative to the FF3M either. These findings imply that DS and TS contain orthogonal information about average returns in the cross-section of individual stocks.

When substituting Size and Book-to-Market for exposures to SMB and HML, the two characteristics are significant at the 1%–level at -3.23 and 2.96, respectively. In the presence

[32] Indeed, the errors-in-variables bias introduced by using estimated exposures ($\widehat{\delta_{i,t}}$) likely causes these regressions to *understate* the importance of intertemporal risk.

of these characteristics, DS exposures are driven out, leaving a small and insignificant DS risk premium of -1.77% ($t = -1.06$). In unreported results, I find that the same result obtains when including Size alone, which again suggests the DS risk premium is a Size effect. In contrast, TS survives and its risk premium remains large and significant at 4.28% ($t = 2.79$). In the full model, that includes both the benchmark factors and their underlying characteristics, the conclusions for DS and TS are largely similar. Moreover, exposures to SMB and HML are driven out, as expected.

These conclusions are robust when we restrict the intercept to zero. In this case, the risk premiums for the factors DS, TS, SMB and HML are slightly larger in absolute value, whereas the MKT risk premium is large and significant, as before. These conclusions are also robust at the monthly frequency in Panel C. The main difference is that the risk premiums for both DS and TS are slightly smaller in absolute value. In case of TS, the difference is small when restricting the intercept to zero. Without this restriction, the TS risk premium remains economically large, but is not always significant. Finally, these conclusions are largely unaltered in the model that also controls for exposures to MOM and PRET. The MOM risk premium is negative, however, which is consistent with the idea that this factor is not a compensation for risk.

To conclude, these cross-sectional regressions suggest DS is largely a Size effect in an ex ante sense. DS mimicking portfolios are long big stocks and short small stocks. As a result, the factor SMB, which loads on Size in the opposite manner, captures a large chunk of the DS risk premium in time-series regressions. Moreover, DS is driven out by the characteristic Size in cross-sectional regressions. In contrast, DS is not driven out by the inclusion of exposures to SMB.

Although, TS and HML are correlated risk factors, for instance, because TS mimicking portfolios load on Value stocks, the positive TS risk premium survives in both time-series and cross-sectional regressions.[33] Similar to SMB, HML is eradicated by its underlying

[33] Another indication that the TS risk premium is robust comes from running cross-sectional regressions within three Size, Book-to-Market or momentum groups, as in Fama and French (2008). I find that the TS risk premium is positive in all nine control groups at over 2.3% and significant at over 5% in seven (except among Big and low Book-to-Market stocks). These results are available upon request.

characteristic in cross-sectional regressions, however. These findings extend Petkova (2006) and Hahn and Lee (2006), who find that TS exposures contain orthogonal information (relative to HML and Book-to-market) in pricing a set of 25 Size and Book-to-Market portfolios, whereas DS exposures do not.

B Alternative ICAPM-motivated state variables

Table VIII is similar to Table VII, but focuses on cross-sectional regressions that ask whether the risk premiums for the alternative state variables are robust to the inclusion of SMB and HML (Model (I)) and, in addition, Size and Book-to-Market (Model (II)). I do not present time-series regressions to conserve space. In sum, these time-series regressions suggest that the risk premiums for RF and CP are captured largely by SMB and HML, similar to DS, whereas the risk premium for VS is not, similar TS.

First, exposures to SMB and HML do not fully drive out exposures to RF, VS and CP in cross-sectional regressions, which is similar to the case of DS and TS. In the quarterly regressions that include an intercept, the risk premiums for RF, VS and CP are economically large at about 3% in absolute value, although the estimate is only significant for VS. At the monthly frequency, the risk premiums for VS and CP strenghten and are significant at -7.06% and 3.43%, respectively.

Second, adding characteristics does not fully drive out RF exposures either. The RF risk premium is insignificant, though economically meaningful when including an intercept at -2.50% at both frequencies. Moreover, the monthly RF risk premium is significant in the specification that restricts the intercept to zero at -3.43% ($t = -2.00$). Although weaker, this pattern is similar to TS, which is perhaps unsurprising, because the two factors are correlated. Indeed, we find that TS|RF has little to add to a specification that already includes TS, even when including the benchmark factors and characteristics.

Although VS is driven out by characteristics at the quarterly frequency, it is not at the monthly frequency with a large and significant VS risk premium of -4.97% ($t = -2.24$) in the full model. Note, the monthly frequency is more relevant for this factor, because the ex post exposure to VS innovations is much larger at this frequency (see Table VI). In contrast, the risk premium for CP is small and insignificant when including characteristics at both frequencies. In unreported results, I find that the eradication of CP is driven quite equally by Size and Book-to-Market. Similarly, Koijen et al. (2013) find that covariances with CP innovations are correlated to Book-to-Market in the cross-section. Finally, for PE and LVL, the risk premiums remain small and insignificant in the presence of the benchmark factors and characteristics, which is similar to DY.

Thus, exposures to DS and CP are driven out unequivocally by characteristics, which suggests these state variables are not separate in an ex ante sense. In contrast, exposures to TS, RF and VS contain orthogonal information about the cross-section of expected returns. This result represents a success for the state variables, in particular, because these exposures are measured with error, whereas the characteristics are measured without error. Following this line of reasoning, a possible explanation for why DS and CP are not driven out by exposures to SMB and HML is that these benchmark exposures also suffer from measurement error.

VI Conclusion

This paper follows a long tradition of papers at the intersection of macroeconomics and asset pricing. I find that the risk premiums for exposure to ICAPM-motivated state variables in the *cross-section* are consistent with how these variables forecast macroeconomic activity in the *time-series*. Following recent advice in the literature, I estimate the risk premiums using stock-level cross-sectional regressions and my evidence suggests this practice is indeed more efficient than using portfolios. This time-series and cross-sectional consistency is an important guard against factor fishing and is consistent with the idea that investors desire to hedge against adverse macroeconomic shocks. Thus, following advice in Cochrane (2005, Ch. 9), I identify "recession state variables".

My method consists of two elements. First, long-horizons regressions establish whether and how a candidate state variable predicts macroeconomic activity. Second, stock-level cross-sectional regressions establish whether a state variables is priced in a consistent manner. I consider four models with different state variables. First and foremost, I focus on a model with the Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). Next, I analyze whether and how the risk-free rate (RF) adds to this model. Third, I consider the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS). Finally, I consider the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and a factor that measures the level of the term-structure (LVL).

I find that DS, RF and VS forecast negative changes in macroeconomic activity, TS and CP forecast positive changes, whereas DY, PE and LVL are not robust predictors. Consistent with this evidence, I estimate stock-level risk premiums that range from -6% to -3% for exposure to DS, RF and VS; that range from 4% to 6% for exposure to TS and CP; and, that are essentially zero for the remaining factors. The risk premiums for the priced state variables translate to Sharpe ratios in the same order of magnitude as the market portfolio: 0.30. I find similar pricing evidence among portfolio sorts, which suggests the state variable risk premiums are investible. Finally, I add to the debate on whether risk exposures or characteristics determine expected returns. I find that the benchmark factors SMB and HML do not eradicate the state variable risk premiums in cross-sectional regressions. Their underlying characteristics Size and Book-to-Market drive out DS, which is largely a Size effect, and CP, however. In contrast, RF, VS and especially TS do contain orthogonal information about the cross-section of expected returns.

A number of extensions come to mind. First, I have largely ignored how exactly the pre- and post-ranking betas vary cross-sectionally and over time, which is relevant for more advanced hedging strategies and portfolio optimization. Second, I leave open the question of how to determine the optimal out-of-sample hedge portfolio, which for most of the state variables in this paper likely loads on bonds. Relatedly, I have not analyzed whether the various ICAPM-models are able to price the cross-section of stocks and (government) bonds simultaneously, as in Koijen et al. (2013).

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Table I: Do DY, DS and TS predict macroeconomic activity?
This table reports the results for single and multiple regressions of current and future industrial production growth (IP) and the Chicago Fed National Activity index (CF) on the Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). Panel A uses quarterly data and considers horizons $S = 0, 1, 2, 4, 8, 20$; Panel B uses monthly data and considers horizons $S = 0, 1, 6, 12, 24, 60$. The original sample is 1962.Q1 to 2011.Q4, and S-1 observations are lost in each of the respective S-horizon regressions. All variables are standardized. The first block of results in each panel presents the single regressions, where I report the slope estimates b_S (which squares equal the regression R^2) and t-ratios using asymptotic Newey-West (in parentheses) and Hansen-Hodrick (in brackets) standard errors computed with S lags. The second block of results in each panel presents the multiple regressions, where I report slope estimates, t-ratios and R^2's.

$$y_{t,t+S} = b'_S z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

Panel A: Quarterly data

		Dividend Yield			Default Spread			Term Spread			
	S	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	R^2
					Single predictive regressions						
IP	0	-0.17	(-2.04)	[-2.05]	-0.45	(-5.70)	[-5.71]	-0.05	(-0.79)	[-0.79]	
	1	-0.19	(-1.73)	[-1.53]	-0.30	(-3.31)	[-2.97]	0.18	(2.04)	[1.89]	
	2	-0.16	(-1.34)	[-1.17]	-0.24	(-2.35)	[-2.09]	0.23	(2.37)	[2.03]	
	4	-0.06	(-0.48)	[-0.42]	-0.13	(-1.07)	[-0.98]	0.28	(2.67)	[2.34]	
	8	0.07	(0.46)	[0.40]	-0.04	(-0.31)	[-0.29]	0.36	(3.43)	[3.02]	
	20	0.15	(0.67)	[0.60]	-0.06	(-0.34)	[-0.31]	0.19	(1.21)	[1.30]	
CF	0	-0.11	(-1.31)	[-1.32]	-0.52	(-6.18)	[-6.20]	-0.11	(-1.81)	[-1.81]	
	1	-0.13	(-1.11)	[-0.95]	-0.35	(-3.12)	[-2.70]	0.12	(1.29)	[1.14]	
	2	-0.09	(-0.74)	[-0.62]	-0.28	(-2.22)	[-1.90]	0.17	(1.70)	[1.43]	
	4	0.00	(-0.02)	[-0.02]	-0.15	(-1.07)	[-0.95]	0.26	(2.44)	[2.12]	
	8	0.13	(0.78)	[0.68]	0.01	(0.10)	[0.10]	0.39	(4.14)	[4.23]	
	20	0.31	(1.49)	[1.75]	0.27	(1.78)	[1.81]	0.18	(1.39)	[1.62]	
					Multiple predictive regressions						
IP	0	0.06	(0.85)	[0.86]	-0.49	(-5.88)	[-5.92]	0.06	(0.94)	[0.95]	0.20
	1	0.04	(0.35)	[0.31]	-0.36	(-3.24)	[-2.93]	0.26	(3.34)	[3.17]	0.14
	2	0.07	(0.53)	[0.47]	-0.33	(-2.58)	[-2.24]	0.31	(4.03)	[3.55]	0.13
	4	0.16	(1.17)	[1.02]	-0.27	(-2.00)	[-1.79]	0.38	(3.98)	[3.56]	0.12
	8	0.32	(1.95)	[1.78]	-0.28	(-1.82)	[-1.67]	0.49	(4.42)	[4.16]	0.20
	20	0.39	(1.29)	[1.17]	-0.30	(-1.08)	[-0.88]	0.32	(2.59)	[2.99]	0.13
CF	0	0.20	(2.56)	[2.58]	-0.62	(-7.17)	[-7.23]	0.02	(0.30)	[0.30]	0.29
	1	0.16	(1.16)	[1.01]	-0.46	(-3.34)	[-2.92]	0.22	(2.81)	[2.56]	0.16
	2	0.18	(1.16)	[0.99]	-0.40	(-2.57)	[-2.18]	0.27	(3.46)	[3.00]	0.13
	4	0.26	(1.63)	[1.36]	-0.33	(-2.03)	[-1.74]	0.37	(4.13)	[3.68]	0.14
	8	0.38	(2.17)	[1.88]	-0.25	(-1.56)	[-1.45]	0.52	(5.16)	[4.91]	0.24
	20	0.35	(1.27)	[1.28]	0.05	(0.22)	[0.20]	0.27	(1.88)	[1.79]	0.16

Table I continued

$$y_{t,t+S} = b'_S z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

Panel B: Monthly data

		Dividend Yield			Default Spread			Term Spread			
	S	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	R^2
					Single predictive regressions						
IP	0	-0.12	(-2.66)	[-2.66]	-0.34	(-6.50)	[-6.51]	0.01	(0.16)	[0.16]	
	1	-0.13	(-2.30)	[-2.02]	-0.31	(-5.35)	[-4.80]	0.06	(1.41)	[1.28]	
	6	-0.14	(-1.35)	[-1.11]	-0.25	(-2.52)	[-2.15]	0.22	(2.46)	[2.01]	
	12	-0.06	(-0.49)	[-0.41]	-0.13	(-1.13)	[-1.00]	0.29	(2.81)	[2.37]	
	24	0.07	(0.47)	[0.40]	-0.04	(-0.30)	[-0.27]	0.37	(3.56)	[3.09]	
	60	0.14	(0.63)	[0.56]	-0.05	(-0.30)	[-0.28]	0.19	(1.23)	[1.29]	
CF	0	-0.10	(-1.96)	[-1.97]	-0.45	(-8.52)	[-8.53]	-0.05	(-1.31)	[-1.31]	
	1	-0.10	(-1.54)	[-1.30]	-0.41	(-5.87)	[-4.98]	0.02	(0.47)	[0.41]	
	6	-0.08	(-0.67)	[-0.53]	-0.29	(-2.48)	[-2.02]	0.17	(1.76)	[1.41]	
	12	0.00	(0.03)	[0.02]	-0.16	(-1.13)	[-0.98]	0.27	(2.54)	[2.13]	
	24	0.14	(0.82)	[0.70]	0.02	(0.10)	[0.11]	0.41	(4.21)	[4.23]	
	60	0.30	(1.43)	[1.68]	0.27	(1.80)	[1.83]	0.19	(1.47)	[1.74]	
					Multiple predictive regressions						
IP	0	0.08	(1.66)	[1.67]	-0.39	(-6.71)	[-6.73]	0.11	(2.65)	[2.66]	0.12
	1	0.08	(1.51)	[1.37]	-0.38	(-5.68)	[-5.12]	0.16	(3.50)	[3.19]	0.11
	6	0.11	(0.95)	[0.78]	-0.37	(-3.01)	[-2.53]	0.33	(4.30)	[3.57]	0.15
	12	0.17	(1.33)	[1.11]	-0.30	(-2.22)	[-1.95]	0.40	(4.43)	[3.78]	0.14
	24	0.33	(2.02)	[1.78]	-0.30	(-2.01)	[-1.76]	0.51	(4.76)	[4.32]	0.22
	60	0.38	(1.25)	[1.12]	-0.30	(-1.06)	[-0.86]	0.33	(2.57)	[2.85]	0.13
CF	0	0.20	(4.18)	[4.19]	-0.56	(-9.84)	[-9.86]	0.09	(2.42)	[2.42]	0.22
	1	0.20	(3.23)	[2.79]	-0.53	(-6.94)	[-5.95]	0.16	(3.26)	[2.82]	0.19
	6	0.22	(1.74)	[1.39]	-0.45	(-3.16)	[-2.56]	0.29	(3.82)	[3.13]	0.16
	12	0.28	(1.89)	[1.52]	-0.36	(-2.27)	[-1.91]	0.40	(4.54)	[3.89]	0.16
	24	0.40	(2.29)	[1.93]	-0.27	(-1.72)	[-1.53]	0.55	(5.57)	[5.08]	0.27
	60	0.34	(1.23)	[1.23]	0.05	(0.23)	[0.21]	0.27	(1.98)	[1.91]	0.17

Table II: Is exposure to DY, DS and TS priced among individual stocks?
This table presents annualized average risk premiums from stock-level cross-sectional regressions for the asset-pricing model with DY, DS and TS as state variables over the period 1967.Q2 to 2011.Q4 (i.e., 179 quarterly and 537 monthly return observations). Row-wise I consider two-factor models that include each state variable next to the CRSP VW market portfolio as well as a joint four-factor model. Regressions of Type (A) include an intercept, whereas Type (B) does not. Panel A uses quarterly data, Panel B uses monthly data and Panel C replaces the $VAR(1)$-innovations in the state variables with their first-differences when estimating the first-stage betas. *, ** and *** indicate significance at the 10, 5 and 1%- level, respectively, using Fama and MacBeth (1973) standard errors. For the four-factor models, the t-statistics are also reported in parentheses. R^2 is the time-series average of the cross-sectional R_t^2's.

Model (A): $r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$; **Model (B)**: $r_{i,t+1} = \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	R^2
		Panel A: Quarterly data				
(A) MKT+DY	8.38***	2.09	0.69			0.028
(A) MKT+DS	8.27***	1.33		-8.15***		0.030
(A) MKT+TS	7.97***	2.33			2.85	0.029
(A) MKT+DY+DS+TS	7.39***	1.49	0.37	-6.56***	5.79***	0.037
	(3.80)	(0.63)	(0.17)	(-2.75)	(3.20)	
(B) MKT+DY		7.99***	1.41			0.016
(B) MKT+DS		7.04**		-8.31***		0.018
(B) MKT+TS		7.74***			3.74*	0.019
(B) MKT+DY+DS+TS		6.61**	1.17	-6.35***	6.93***	0.026
		(2.43)	(0.47)	(-2.60)	(3.75)	
		Panel B: Monthly data				
(A) MKT+DY	9.58***	0.30	3.45			0.021
(A) MKT+DS	9.27***	0.72		-6.18**		0.022
(A) MKT+TS	9.19***	0.81			3.48	0.022
(A) MKT+DY+DS+TS	8.23***	0.78	1.54	-5.28***	5.49***	0.027
	(5.13)	(0.32)	(0.54)	(-2.21)	(2.69)	
(B) MKT+DY		7.98***	4.55			0.015
(B) MKT+DS		7.97***		-5.44**		0.016
(B) MKT+TS		7.82***			6.06***	0.015
(B) MKT+DY+DS+TS		7.18***	3.43	-4.61*	7.62***	0.021
		(2.78)	(1.18)	(-1.92)	(3.77)	
		Panel C: First-differences in state variables				
				Quarterly data		
(A) MKT+DY+DS+TS	7.76***	1.09	-0.18	-5.47***	2.34	0.037
	(3.98)	(0.43)	(-0.07)	(-2.86)	(1.43)	
(B) MKT+DY+DS+TS		6.63**	-5.99**	-5.15***	4.16**	0.027
		(2.38)	(-2.24)	(-2.64)	(2.45)	
				Monthly data		
(A) MKT+DY+DS+TS	8.34***	0.83	0.29	-4.93**	4.15**	0.026
	(5.08)	(0.30)	(0.11)	(-2.40)	(2.01)	
(B) MKT+DY+DS+TS		7.52***	-7.20***	-4.28**	7.07***	0.022
		(2.87)	(-2.80)	(-2.06)	(3.34)	

Table III: Predicting macroeconomic activity with alternative state variables
This table presents multiple regressions of macroeconomic activity (measured either with Industrial Production growth (IP) or the Chicago Fed National Activity Index (CF)) on alternative sets of ICAPM-motivated state variables. Model (1) replaces TS with RF. Model (2) includes RF (orthogonalized from TS) next to DY, DS and TS. Model (3) uses the state variables of Campbell and Vuolteenaho (2004): TS, PE and VS. Model (4) uses the state variables of Koijen et al. (2013): CP and LVL. (See Section II for a description of the variables.) The regressions use quarterly data and consider three horizons $S = 1, 4, 8$. *, ** and *** indicate significance at the 10%, 5% and 1%-level, respectively, using the more conservative Hansen and Hodrick (1980) asymptotic standard errors with S lags.

$$y_{t,t+S} = b'_S z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

	S	$b_{DY,S}$	$b_{DS,S}$	$b_{TS,S}$	$b_{RF,S}$ / $b_{RF\|TS,S}$	$b_{PE,S}$	$b_{VS,S}$	$b_{CP,S}$	$b_{LVL,S}$	R^2
					(1) $z_t = (DY_t, DS_t, RF_t)'$					
IP	1	-0.02	-0.27**		-0.07					0.09
	4	0.27	-0.14		-0.41***					0.10
	8	0.52**	-0.09		-0.61***					0.21
CF	1	0.04	-0.38**		0.01					0.12
	4	0.31	-0.24		-0.29					0.06
	8	0.52***	-0.13		-0.47**					0.12
					(2) $z_t = (DY_t, DS_t, TS_t, RF_t\|TS_t)'$					
IP	1	-0.05	-0.40***	0.24***	0.16					0.15
	4	0.25	-0.24	0.40***	-0.16					0.13
	8	0.49**	-0.20	0.54***	-0.32*					0.25
CF	1	-0.05	-0.47***	0.19**	0.29					0.20
	4	0.22	-0.33*	0.37***	0.05					0.13
	8	0.41**	-0.24	0.53***	-0.03					0.24
					(3) Campbell and Vuolteenaho (2004): $z_t = (TS_t, PE_t, VS_t)'$					
IP	1			0.20**		0.20*	-0.16**			0.06
	4			0.30**		0.09	-0.12			0.08
	8			0.36***		-0.08	0.02			0.12
CF	1			0.19*		0.20	-0.34***			0.09
	4			0.34***		0.06	-0.31***			0.14
	8			0.45***		-0.16	-0.16			0.21
					(4) Koijen et al. (2013): $z_t = (CP_t, LVL_t)'$					
IP	1							0.14	-0.15	0.03
	4							0.14	-0.22	0.05
	8							0.33***	-0.24*	0.14
CF	1							0.11	-0.01	0.01
	4							0.17*	-0.05	0.02
	8							0.40***	-0.04	0.15

Table IV: Firm-level risk premiums for alternative state variables

Row-wise this table presents annualized average risk premiums among individual stocks. Each quarter (Panel A) or month (Panel B) risk premiums are estimated with the two-stage cross-sectional regression method of Fama and MacBeth (1973). I consider multi-factor asset-pricing models that include the CRSP VW market portfolio and one of four different sets of ICAPM-motivated state variables z_t. In Model (1), I substitute RF for TS, such that $z_t = (DY_t, DS_t, RF_t)'$. In Model (2), I include both TS and RF, but orthogonalize RF from TS first, such that $z_t = (DY_t, DS_t, TS_t, RF_t|TS_t)'$. Model (3) follows Campbell and Vuolteenaho (2004) and defines $z_t = (TS_t, PE_t, VS_t)'$. Model (4) follows Koijen et al. (2013) and defines $z_t = (CP_t, LVL_t)'$. For each model, I present cross-sectional regressions with and without an intercept (Type (A) and (B), respectively). For each cross-sectional risk premium estimate, corresponding Fama and MacBeth (1973) t-statistics are presented underneath each estimate in parentheses. R^2 is the time-series average of the cross-sectional R^2_t.

Model (A): $r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$; **Model (B)**: $r_{i,t+1} = \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	λ_{RF} / $\lambda_{RF\|TS}$	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	R^2
						Panel A: Quarterly data					
(1.A)	7.87	1.34	-0.78	-7.70		-3.64					0.037
	(4.05)	(0.58)	(-0.37)	(-3.16)		(-1.77)					
(1.B)		6.90	-0.01	-7.70		-3.86					0.026
		(2.53)	(0.00)	(-3.04)		(-1.84)					
(2.A)	7.33	1.89	-1.13	-7.33	5.50	1.43					0.040
	(3.87)	(0.83)	(-0.58)	(-3.11)	(3.26)	(0.61)					
(2.B)		6.92	-0.50	-7.21	6.73	2.65					0.029
		(2.61)	(-0.23)	(-3.00)	(3.85)	(1.05)					
(3.A)	7.21	2.92			3.02		1.67	-5.23			0.036
	(3.77)	(1.19)			(1.59)		(0.82)	(-2.56)			
(3.B)		7.98			4.07		1.33	-5.50			0.026
		(2.80)			(2.10)		(0.63)	(-2.74)			
(4.A)	8.37	1.77							4.21	2.35	0.032
	(4.48)	(0.75)							(2.23)	(0.93)	
(4.B)		7.56							4.84	2.08	0.022
		(2.71)							(2.54)	(0.78)	
						Panel B: Monthly data					
(1.A)	8.38	0.89	-0.02	-6.00		-3.28					0.027
	(5.20)	(0.35)	(-0.01)	(-2.51)		(-1.45)					
(1.B)		7.47	1.69	-5.26		-4.94					0.022
		(2.85)	(0.57)	(-2.18)		(-2.20)					
(2.A)	8.27	0.66	-0.03	-5.65	5.09	1.64					0.029
	(5.17)	(0.27)	(-0.01)	(-2.45)	(2.61)	(0.77)					
(2.B)		6.99	1.59	-4.82	7.43	2.18					0.024
		(2.75)	(0.55)	(-2.08)	(3.79)	(1.01)					
(3.A)	8.40	1.33			3.85		2.99	-8.63			0.027
	(5.25)	(0.55)			(1.92)		(1.51)	(-3.44)			
(3.B)		7.89			5.95		3.80	-10.07			0.022
		(3.08)			(2.98)		(1.86)	(-3.91)			
(4.A)	9.25	0.57							5.85	1.07	0.025
	(5.68)	(0.23)							(2.64)	(0.43)	
(4.B)		7.79							7.03	-1.10	0.019
		(3.03)							(3.10)	(-0.44)	

Table V: Pre- and post-ranking analysis of DY, DS and TS mimicking portfolios This table presents the portfolios that are implicit in the cross-sectional regression procedure, denoted FMB, in more detail. As a benchmark, the table also presents results for market value-weighted portfolios, that is, a one-dimensional sort in five quintiles (MV, H to MV, L) as well as the resulting spreading portfolio ($HLMV$), and an equal-weighted spreading portfolio ($HLEW$). Panel A presents (i) post-ranking exposures $(\beta_m, \delta')'$ from the four-factor model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t})' + u_t$, (where standard errors are Newey-West with lag length one), (ii) average pre-ranking exposure within the portfolio, and (iii) annualized performance (average return, standard deviation and Sharpe ratio). Panel B focuses solely on the three mimicking strategies and presents pre-ranking characteristics: Size ($ billion), Book-to-Market and Momentum, which are weighted cross-sectional averages (and where standard errors are Newey-West with lag length ten), as well as HH, which is a cross-sectional Herfindahl-index, and annualized Turnover. Wherever necessary *, ** and *** indicate significance at the 10, 5 and 1% -level, respectively.

Panel A: Exposures and unconditional performance

	Post-ranking exposures						Pre-rank.	Avg.	St.	Sharpe
	α	β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2	exposure	ret.	dev.	ratio
				Dividend Yield mimicking portfolios						
MV, H	0.00	1.31***	0.22***	0.03	-0.12***	0.87	0.52	6.55*	25.76	0.25
$MV, 2$	0.00	1.07***	0.02	0.03	-0.01	0.90	0.21	7.14**	20.26	0.35
$MV, 3$	0.00	0.93***	0.01	0.04**	0.02*	0.94	0.05	5.89**	17.30	0.34
$MV, 4$	0.00**	0.85***	-0.04**	-0.02	0.00	0.93	-0.10	5.89**	15.90	0.37
MV, L	0.00	1.01***	-0.01	-0.02	0.02	0.88	-0.36	6.70**	19.32	0.35
$HLMV$	0.00	0.30***	0.22***	0.05	-0.14***	0.23	0.88	-0.15	14.96	-0.01
$HLEW$	0.00	0.09*	0.11*	0.06	-0.03	0.05	0.99	0.65	10.85	0.06
FMB	0.00	0.16**	0.29***	-0.04	0.00	0.17	1.00	0.37	14.43	0.03
				Default Spread mimicking portfolios						
MV, H	0.00	1.03***	0.10**	0.06**	-0.06*	0.88	0.32	5.77*	19.87	0.29
$MV, 2$	0.00	0.89***	0.00	0.02	0.04	0.94	0.05	5.08**	16.53	0.31
$MV, 3$	0.00**	0.94***	-0.05	0.01	0.00	0.89	-0.12	6.95***	17.94	0.39
$MV, 4$	0.01**	1.11***	0.00	0.01	0.03	0.87	-0.29	8.25***	21.41	0.39
MV, L	0.00	1.31***	0.10*	-0.05	0.06	0.82	-0.62	7.61*	26.05	0.29
$HLMV$	0.00	-0.28***	0.01	0.11**	-0.12*	0.12	0.94	-1.84	15.20	-0.12
$HLEW$	-0.01**	-0.17**	0.03	0.08**	-0.03	0.05	1.02	-4.59**	12.97	-0.35
FMB	-0.01***	-0.21**	-0.02	0.32**	-0.04	0.17	1.00	-6.56***	15.93	-0.41
				Term Spread mimicking portfolios						
MV, H	0.01	1.13***	0.10*	-0.09**	0.11***	0.80	0.60	8.02**	22.95	0.35
$MV, 2$	0.01*	1.01***	0.03	-0.01	0.04	0.88	0.29	7.55***	19.40	0.39
$MV, 3$	0.00	0.93***	-0.04	0.00	0.04**	0.92	0.11	5.83**	17.32	0.34
$MV, 4$	0.00	0.93***	-0.01	0.05***	-0.03	0.93	-0.05	4.99*	17.32	0.29
MV, L	-0.01**	1.05***	0.06	0.03	-0.05**	0.87	-0.30	3.13	20.18	0.16
$HLMV$	0.01*	0.08	0.04	-0.11**	0.16***	0.04	0.90	4.90**	14.50	0.34
$HLEW$	0.02***	-0.05	-0.04	-0.05	0.10**	0.03	1.02	5.62***	10.35	0.54
FMB	0.01***	-0.02	-0.02	0.02	0.17**	0.06	1.00	5.79***	12.12	0.48

Table V continued

Panel B: Pre-ranking portfolio characteristics

	Size	Book-to-Market	Momentum	HH	Turnover
		Dividend Yield mimicking portfolios			
HLMV	-16.23**	0.10*	6.92	0.062	1.673
HLEW	-0.96***	0.11*	1.54	0.004	1.837
FMB	-1.38***	0.13*	4.92	0.008	1.482
		Default Spread mimicking portfolios			
HLMV	8.19	-0.20**	-9.79	0.074	1.595
HLEW	0.91***	-0.36***	0.01	0.004	1.702
FMB	1.13***	-0.43***	2.45	0.006	1.492
		Term Spread mimicking portfolios			
HLMV	-8.46	0.20***	0.44	0.070	1.556
HLEW	-1.29***	0.17***	-0.26	0.004	1.746
FMB	-0.82***	0.15***	1.93	0.009	1.460

Table VI: Mimicking portfolios for alternative state variables

This table presents the portfolios that are implicit in the cross-sectional regression procedure, denoted FMB, and the benchmark spreading portfolios ($HLMV$ and $HLEW$) for the alternative sets of state variables. Panel A presents results for the model where $z_t = (DY_t, DS_t, RF_t)'$; Panel B for $z_t = (TS_t, PE_t, VS_t)'$ as in Campbell and Vuolteenaho (2004); and, Panel C for $z_t = (CP_t, LVL_t)'$ as in Koijen et al. (2013). Focusing solely on the mimicking portfolios for the alternative state variables that are priced in Table IV: RF, PE, VS, CP and LVL, I report (i) post-ranking exposures $(\beta_m, \delta')'$ from the model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta' \varepsilon_{z_t}^{Full} + u_t$, (where standard errors are Newey-West with lag length one) and (ii) annualized performance (average return, standard deviation and Sharpe ratio). *, ** and *** indicate significance at the 10, 5 and 1%- level, respectively.

Panel A: $z_t = (DY_t, DS_t, RF_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{DY_t}^{Full}, \varepsilon_{DS_t}^{Full}, \varepsilon_{RF_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{DY}	δ_{DS}	δ_{RF}	R^2	ret.	dev.	ratio
				RF mimicking portfolios					
HLMV	-0.01**	-0.09	0.01	0.00	0.16**	0.03	-4.59**	14.09	-0.33
HLEW	-0.02***	-0.01	0.06	0.01	0.12*	0.03	-6.34***	11.15	-0.57
FMB	-0.01**	0.09	0.02	-0.02	0.20**	0.08	-3.64*	13.79	-0.26

Panel B: Campbell and Vuolteenaho (2004): $z_t = (TS_t, PE_t, VS_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{TS_t}^{Full}, \varepsilon_{PE_t}^{Full}, \varepsilon_{VS_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{TS}	δ_{PE}	δ_{VS}	R^2	ret.	dev.	ratio
				PE mimicking portfolios					
HLMV	0.00	-0.02	0.04	0.05	-0.20***	0.06	-0.56	13.59	-0.04
HLEW	0.00	0.03	-0.02	0.08*	-0.09	0.02	0.44	11.29	0.04
FMB	0.01	-0.04	-0.04	0.19**	-0.11	0.07	1.67	13.57	0.12
				VS mimicking portfolios					
HLMV	-0.01	0.35***	-0.12*	0.01	0.21**	0.18	-1.72	17.53	-0.10
HLEW	-0.01***	0.20***	-0.03	-0.04	0.11	0.12	-3.79**	11.20	-0.34
FMB	-0.02***	0.24***	-0.03	-0.05	0.10	0.11	-5.23**	13.67	-0.38

Panel C: Koijen et al. (2013): $z_t = (CP_t, LVL_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{CP_t}^{Full}, \varepsilon_{LVL_t}^{Full})' + u_t$					Avg.	St.	Sharpe
	α	β_m	δ_{CP}	δ_{LVL}	R^2	ret.	dev.	ratio
				CP mimicking portfolios				
HLMV	0.00	0.31***	0.12***	0.05	0.17	3.24	14.15	0.23
HLEW	0.01	0.11*	0.03	0.01	0.02	2.98*	10.62	0.28
FMB	0.01**	0.02	0.07	-0.08	0.01	4.21**	12.60	0.33
				LVL mimicking portfolios				
HLMV	-0.01	0.55***	0.12**	0.31***	0.39	0.98	18.12	0.05
HLEW	0.00	0.36***	0.08	0.23***	0.29	1.41	14.06	0.10
FMB	0.00	0.34***	0.11	0.32***	0.24	2.35	16.90	0.14

Table VII: Are DY, DS and TS risk premiums captured by the factors and characteristics of Fama and French (1992, 1993)?

This table analyzes whether the risk premiums for DY, DS and TS can be captured by the benchmark factors SMB and HML (and MOM) as well as their underlying characteristics Size and Book-to-Market (and Prior return). To this end, Panel A presents time-series regressions of the Fama and MacBeth (1973) cross-sectional regression risk premiums (from Table II) on the Fama and French (1993) three-factor model (FF3M) as well as the Carhart (1997) four-factor model (FFCM) using both quarterly and monthly data. t-statistics based on Newey-West standard errors with lag length one are in parentheses. Next, I present cross-sectional regressions that additionally include the benchmark factors and characteristics at the quarterly frequency (Panel B) and the monthly frequency (Panel C). Model (1) presents results for the FF3M. Model (2) adds the state variables. Model (3) adds the state variables to the characteristics Size and Book-to-Market instead. Model (4) includes the state variables, SMB, HML, Size and Book-to-Market. Model (5) adds to this model the MOM factor and the Momentum characteristic. Throughout, Type (A) includes an intercept, whereas Type (B) restricts the intercept to zero. For each cross-sectional regression, the table presents the unconditional average annualized risk premiums $\lambda = \frac{1}{T}\sum_t \widehat{\lambda_t}$, with Fama and MacBeth (1973) $t-$statistics in parentheses, and the average cross-sectional $R^2 = \frac{1}{T}\sum_t R_t^2$.

Panel A: Time-series regressions

$$r_{FMB(k),t} = \alpha + \beta_m r_{m,t} + \beta_{smb} r_{smb,t} + \beta_{hml} r_{hml,t} + (\beta_{mom} r_{mom,t}) + \varepsilon_t$$

Quarterly data						Monthly data					
α	β_m	β_{smb}	β_{hml}	β_{mom}	R^2	α	β_m	β_{smb}	β_{hml}	β_{mom}	R^2
Dividend Yield mimicking portfolio ($FMB(DY)$)											
0.25	0.02	0.34	-0.19		0.10	1.03	0.10	0.46	-0.27		0.14
(0.13)	(0.24)	(2.43)	(-1.82)			(0.37)	(1.44)	(3.72)	(-2.05)		
1.69	0.00	0.30	-0.23	-0.12	0.11	4.26	0.05	0.46	-0.37	-0.29	0.19
(0.76)	(-0.02)	(2.11)	(-2.11)	(-1.26)		(1.31)	(0.70)	(4.04)	(-2.77)	(-2.19)	
Default Spread mimicking portfolio ($FMB(DS)$)											
-2.89	-0.12	-0.56	-0.32		0.22	-2.22	-0.14	-0.58	-0.17		0.19
(-1.38)	(-1.15)	(-5.44)	(-2.60)			(-1.01)	(-2.32)	(-6.35)	(-1.64)		
-5.26	-0.08	-0.49	-0.26	0.20	0.25	-4.38	-0.11	-0.57	-0.11	0.20	0.23
(-1.27)	(-1.03)	(-3.73)	(-2.09)	(0.86)		(-1.75)	(-1.90)	(-6.76)	(-1.18)	(2.30)	
Term Spread mimicking portfolio ($FMB(TS)$)											
4.20	0.06	-0.05	0.29		0.06	3.10	-0.03	0.18	0.45		0.11
(2.33)	(0.85)	(-0.50)	(2.94)			(1.49)	(-0.47)	(2.29)	(4.26)		
4.72	0.05	-0.07	0.28	-0.04	0.06	3.76	-0.04	0.18	0.43	-0.06	0.12
(2.78)	(0.76)	(-0.65)	(2.87)	(-0.58)		(1.78)	(-0.68)	(2.28)	(4.19)	(-1.20)	

Table VII continued

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda'_{f,t}(\widehat{\beta_{i,smb,t}}, \widehat{\beta_{i,hml,t}}, \widehat{\beta_{i,mom,t}})' + \lambda'_{c,t}(Size_{i,t}, BM_{i,t}, PRET_{i,t})' + \upsilon_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	λ_{smb}	λ_{hml}	λ_{mom}	λ_{Size}	λ_{BM}	λ_{PRET}	R^2
					Panel B: Cross-sectional regressions - Quarterly data							
(1.A)	6.95	1.58				1.91	2.63					0.042
	(3.77)	(0.67)				(1.24)	(2.03)					
(1.B)		6.54				3.33	2.03					0.035
		(2.54)				(2.04)	(1.54)					
(2.A)	6.69	1.78	0.39	-5.58	4.20	2.17	2.24					0.048
	(3.58)	(0.82)	(0.22)	(-2.52)	(2.61)	(1.41)	(1.78)					
(2.B)		6.56	0.60	-5.21	4.95	3.57	1.64					0.040
		(2.64)	(0.30)	(-2.41)	(3.05)	(2.16)	(1.29)					
(3.A)	7.50	2.59	-1.34	-1.77	4.28				-3.23	2.96		0.059
	(3.74)	(1.22)	(-0.71)	(-1.06)	(2.79)				(-2.72)	(4.35)		
(3.B)		7.68	-0.22	-2.30	5.08				-2.87	3.22		0.049
		(2.75)	(-0.10)	(-1.20)	(3.26)				(-2.52)	(4.73)		
(4.A)	7.17	3.58	-0.80	-1.92	3.32	0.39	0.18		-3.53	2.68		0.066
	(3.69)	(1.72)	(-0.47)	(-1.13)	(2.29)	(0.33)	(0.16)		(-3.12)	(4.21)		
(4.B)		8.42	-0.10	-2.25	3.78	2.06	-0.24		-3.22	2.86		0.057
		(3.20)	(-0.05)	(-1.21)	(2.59)	(1.49)	(-0.21)		(-2.92)	(4.55)		
(5.A)	7.98	2.56	-0.02	-2.56	2.54	0.56	-0.26	-2.20	-3.61	2.75	0.87	0.073
	(3.81)	(1.38)	(-0.01)	(-1.79)	(2.00)	(0.51)	(-0.26)	(-2.02)	(-3.38)	(4.42)	(1.04)	
(5.B)		7.95	1.10	-3.35	3.17	2.53	-0.58	-3.20	-3.11	2.96	0.42	0.065
		(3.07)	(0.61)	(-1.87)	(2.55)	(1.83)	(-0.54)	(-2.52)	(-3.03)	(4.76)	(0.54)	
					Panel C: Cross-sectional regressions - Monthly							
(1.A)	8.09	-0.12				1.70	3.16					0.035
	(5.50)	(-0.05)				(1.12)	(2.12)					
(1.B)		6.28				2.97	3.12					0.031
		(2.63)				(1.90)	(2.08)					
(2.A)	7.66	0.12	0.39	-4.56	3.46	1.62	2.93					0.040
	(5.18)	(0.05)	(0.16)	(-2.42)	(1.91)	(1.08)	(2.03)					
(2.B)		6.15	1.71	-4.05	4.64	2.85	2.89					0.036
		(2.60)	(0.67)	(-2.15)	(2.58)	(1.84)	(1.99)					
(3.A)	7.27	2.81	0.97	-0.33	2.84				-4.11	2.55		0.044
	(4.57)	(1.19)	(0.38)	(-0.18)	(1.65)				(-3.77)	(4.67)		
(3.B)		8.32	2.61	-0.05	4.77				-4.03	2.76		0.039
		(3.15)	(1.00)	(-0.03)	(2.69)				(-3.76)	(4.90)		
(4.A)	7.39	4.34	1.28	-1.44	2.59	-1.89	0.14		-4.85	2.35		0.050
	(4.91)	(1.96)	(0.54)	(-0.84)	(1.58)	(-1.54)	(0.11)		(-4.81)	(5.11)		
(4.B)		10.06	2.77	-1.26	3.69	-0.67	0.17		-4.85	2.38		0.047
		(4.12)	(1.12)	(-0.73)	(2.22)	(-0.52)	(0.12)		(-4.86)	(5.24)		
(5.A)	7.97	4.09	2.14	-1.67	2.36	-2.23	-0.27	-2.56	-5.41	2.29	2.59	0.057
	(5.14)	(1.98)	(1.00)	(-1.01)	(1.60)	(-1.88)	(-0.22)	(-1.81)	(-5.68)	(4.98)	(4.11)	
(5.B)		10.31	3.85	-1.61	3.52	-0.82	-0.23	-3.18	-5.36	2.35	2.38	0.054
		(4.36)	(1.74)	(-0.95)	(2.38)	(-0.65)	(-0.18)	(-2.15)	(-5.68)	(5.16)	(3.90)	

Table VIII: Are risk premiums for the alternative state variables captured by the factors and characteristics of Fama and French (1992, 1993)?

This table analyzes whether the stock-level risk premiums for exposure to the alternative state variables are captured by exposure to the benchmark factors (SMB and HML) or their underlying characteristics (Size and Book-to-Market) at the quarterly frequency (Panel A) and the monthly frequency (Panel B). Row-wise the triplet (a,b,c) defines the specification. "a" defines the set of state variables included next to the CRSP VW market return: (1) $z_t = (DY_t, DS_t, RF_t)'$; (2) $z_t = (DY_t, DS_t, TS_t, RF_t|TS_t)'$; (3) $z_t = (TS_t, PE_t, VS_t)'$ as in Campbell and Vuolteenaho (2004); and, (4) $z_t = (CP_t, LVL_t)'$ as in Koijen et al. (2013). "b" defines the whether an intercept is included (A) or not (B). "c" defines the benchmark variables that are included, that is, either (I) exposures to SMB and HML or (II) both exposures to SMB and HML and characteristics Size and Book-to-Market . For each cross-sectional regression, the table presents the annualized unconditional average risk premium $\lambda = \frac{1}{T}\sum_t \widehat{\lambda}_t$ (where *, ** and *** indicate significance at the 10, 5 and 1%-level, respectively, using Fama and MacBeth (1973) standard errors) and R^2, which is the time-series average of the cross-sectional R_t^2.

Panel A: Quarterly data

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda'_{f,t}(\widehat{\beta_{i,smb,t}}, \widehat{\beta_{i,hml,t}})' + \lambda'_{c,t}(Size_{i,t}, BM_{i,t})' + v_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	$\lambda_{RF}/\lambda_{RF\|TS}$	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	λ_{smb}	λ_{hml}	λ_{Size}	λ_{BM}	R^2
(1.A.I)	6.80***	1.66	-0.57	-6.28***		-2.82					2.10	2.22*			0.047
(1.B.I)		6.59***	-0.57	-6.00***		-2.91					3.46**	1.65			0.040
(1.A.II)	7.30***	3.45*	-1.85	-2.58		-2.24					0.32	0.10	-3.55***	2.74***	0.065
(1.B.II)		8.45***	-1.37	-3.02		-1.94					1.98	-0.30	-3.23***	2.90***	0.057
(2.A.I)	6.72***	1.74	-0.93	-5.85***	4.62***	1.58					2.16	2.13*			0.050
(2.B.I)		6.52***	-0.89	-5.50**	5.49***	2.54					3.57**	1.56			0.042
(2.A.II)	7.45***	3.42*	-2.27	-2.35	3.68**	0.92					0.30	0.01	-3.65***	2.73***	0.067
(2.B.II)		8.43***	-1.76	-2.73	4.25***	2.12					2.06	-0.39	-3.31***	2.89***	0.059
(3.A.I)	6.56***	2.03			2.48		0.45	-3.18*			2.02	2.37*			0.048
(3.B.I)		6.77***			3.32**		0.35	-3.45**			3.39**	1.67			0.040
(3.A.II)	7.06***	3.79*			1.78		0.54	-1.10			0.30	0.24	-3.56***	2.62***	0.066
(3.B.II)		8.67***			2.25		0.46	-1.53			1.91	-0.27	-3.26***	2.81***	0.058
(4.A.I)	6.80***	1.67							2.49	0.91	2.09	2.49*			0.046
(4.B.I)		6.39**							2.71*	0.46	3.59**	1.96			0.039
(4.A.II)	7.24***	3.57*							1.11	-0.48	0.33	0.39	-3.63***	2.69***	0.064
(4.B.II)		8.33***							1.28	-0.31	2.11	0.03	-3.28***	2.87***	0.056

Table VIII continued

Panel B:Monthly data

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda'_{f,t}(\widehat{\beta_{i,smb,t}}, \widehat{\beta_{i,hml,t}})' + \lambda'_{c,t}(Size_{i,t}, BM_{i,t})' + \upsilon_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	$\lambda_{RF}/\lambda_{RF\|TS}$	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	λ_{smb}	λ_{hml}	λ_{Size}	λ_{BM}	R^2
(1.A.I)	7.77***	0.13	-1.31	-5.05***		-1.82					1.59	2.92**			0.040
(1.B.I)		6.27***	-0.29	-4.51**		-2.83					2.78*	2.85*			0.037
(1.A.II)	7.55***	4.30*	-0.80	-1.79		-2.51					-1.96	0.08	-4.90***	2.39***	0.051
(1.B.II)		10.16***	0.40	-1.60		-3.43**					-0.76	0.07	-4.90***	2.42***	0.047
(2.A.I)	7.83***	0.02	-0.93	-4.68**	3.41*	1.98					1.43	2.90**			0.041
(2.B.I)		6.16***	0.12	-4.15**	4.72***	2.12					2.66*	2.84*			0.038
(2.A.II)	7.63***	4.23*	-0.22	-1.73	2.55	-0.48					-2.09*	0.05	-4.87***	2.41***	0.052
(2.B.II)		10.12***	1.05	-1.54	3.77**	-0.34					-0.85	0.06	-4.86***	2.44***	0.048
(3.A.I)	8.13***	-0.24			2.62		0.55	-7.06***			1.68	3.21**			0.038
(3.B.I)		6.17***			3.81**		0.82	-7.53***			3.02*	3.15**			0.035
(3.A.II)	7.68***	4.09*			1.57		-0.40	-4.97**			-1.80	0.43	-4.89***	2.27***	0.050
(3.B.II)		10.01***			2.69		-0.16	-5.39***			-0.47	0.40	-4.89***	2.33***	0.046
(4.A.I)	8.09***	-0.10							3.43**	0.53	1.74	3.10**			0.038
(4.B.I)		6.26***							3.64**	-1.36	3.08**	3.01**			0.035
(4.A.II)	7.79***	4.15*							1.60	-1.68	-1.90	0.32	-5.00***	2.23***	0.049
(4.B.II)		10.17***							1.72	-3.46*	-0.54	0.25	-4.97***	2.32***	0.046

Internet Appendix

Table A: Pricing of the Gilchrist and Zakrajsek (2012) measure of default risk relative to DS

This table is similar to Table II, but presents annualized average risk premiums from stock-level cross-sectional regressions for two four-factor models, with the set of state variables including DY, DS and TS in Model (1) and DY, TS and the Gilchrist and Zakrajsek (2012) measure of default risk, denoted DSGZ in Model (2). The sample period is 1978.Q2 to 2010.Q3 (i.e., 130 quarterly and 392 monthly return observations in Panels A and B, respectively). I present the average annualized risk premiums with corresponding t-statistics based on Fama and MacBeth (1973) standard errors in parentheses underneath. R^2 is the time-series average of the cross-sectional R_t^2's. Finally, in each panel, I present the correlation between the time-series of estimated risk premiums for DS in Model (1) and DSGZ in Model (2).

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	λ_{DSGZ}	R^2
			Panel A: Quarterly data				
(1)	7.99	2.14	3.35	-5.83	4.31		0.025
	(3.54)	(0.84)	(1.38)	(-2.18)	(2.05)		
(2)	8.89	1.76	3.28		3.53	-5.89	0.027
	(3.95)	(0.68)	(1.41)		(2.08)	(-2.00)	
			$Corr(\lambda_{DS,t}, \lambda_{DSGZ,t}) = 0.75$				
			Panel B: Monthly data				
(1)	8.51	1.82	5.41	-4.86	5.64		0.023
	(4.50)	(0.62)	(1.61)	(-1.88)	(2.57)		
(2)	8.65	1.78	-0.72		4.57	-4.04	0.022
	(4.65)	(0.57)	(-0.23)		(1.95)	(-1.85)	
			$Corr(\lambda_{DS,t}, \lambda_{DSGZ,t}) = 0.53$				

Table B: Quarterly cross-sectional regressions with alternative measures of state variable innovations

This table presents stock-level risk premiums for the ICAPM-motivated state variables when innovations are alternatively measured with first-differences (Panel A) or using a $VAR(2)$ (Panel B). I consider multi-factor asset-pricing models that include the CRSP VW market portfolio and one of four different sets of ICAPM-motivated state variables z_t: (1) $z_t = (DY_t, DS_t, TS_t)'$, (2) $z_t = (DY_t, DS_t, RF_t)'$, (3) $z_t = (TS_t, PE_t, VS_t)'$ and (4) $z_t = (CP_t, LVL_t)'$. Risk premiums are estimated with the two-stage cross-sectional regression method of Fama and MacBeth (1973) at the quarterly frequency and including an intercept. R^2 is the time-series average of the cross-sectional R_t^2.

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	λ_{RF}	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	R^2
					Panel A: First-differences in the state variables						
(1)	7.76	1.09	-0.18	-5.47	2.34						0.04
	(3.98)	(0.43)	(-0.07)	(-2.86)	(1.43)						
(2)	7.46	1.55	-0.66	-5.48		-2.33					0.04
	(3.83)	(0.61)	(-0.26)	(-2.88)		(-1.22)					
(3)	7.04	2.82			1.33		4.44	-4.21			0.04
	(3.63)	(1.01)			(0.84)		(1.45)	(-2.14)			
(4)	8.49	1.61							2.66	2.31	0.03
	(4.49)	(0.70)							(1.76)	(1.10)	
					Panel B: VAR(2)-innovations in the state variables						
(1)	7.52	1.35	3.71	-5.26	4.98						0.04
	(3.84)	(0.55)	(1.90)	(-2.29)	(2.65)						
(2)	7.91	1.67	1.19	-7.21		-2.09					0.04
	(4.07)	(0.69)	(0.64)	(-2.98)		(-1.06)					
(3)	7.12	2.80			2.00		1.08	-5.03			0.04
	(3.74)	(1.19)			(1.09)		(0.50)	(-2.49)			
(4)	8.35	1.85							3.39	2.35	0.03
	(4.39)	(0.78)							(1.82)	(1.03)	

Table C: Pre- and post-ranking analysis of DY, DS and TS mimicking portfolios at the monthly frequency

This table is the equivalent of Table V, but presents results for the monthly frequency. The mimicking portfolios of interest are are FMB, which is implicit in the cross-sectional regression procedure, as well as market value- and equal-weighted portfolios from a one-dimensional sort in five quintiles and their resulting spreading portfolios ($HLMV$ and $HLEW$). Panel A presents (i) post-ranking exposures $(\beta_m, \delta')'$ from the four-factor model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t})' + u_t$, (where standard errors are Newey-West with lag length one), (ii) average pre-ranking exposure within the portfolio, and (iii) annualized performance (average return, standard deviation and Sharpe ratio). Panel B focuses solely on the three mimicking strategies and presents pre-ranking characteristics: Size ($ billion), Book-to-Market and Momentum, which are weighted cross-sectional averages (and where standard errors are Newey-West with lag length thirty), as well as HH, which is a cross-sectional Herfindahl-index, and annualized Turnover. Wherever necessary *, ** and *** indicate significance at the 10, 5 and 1% -level, respectively.

Panel A: Exposures and unconditional performance

	Post-ranking exposures						Pre-rank.	Avg.	St.	Sharpe
	α	β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2	exposure	ret.	dev.	ratio
				Dividend Yield mimicking portfolios						
MV, H	0.00	1.27***	0.16***	-0.02	0.05*	0.82	0.33	6.13*	22.72	0.27
$MV, 2$	0.00	1.11***	0.08***	-0.04**	0.03	0.87	0.13	6.48**	19.28	0.34
$MV, 3$	0.00	0.93***	-0.01	0.01	0.01	0.89	0.02	4.88**	15.95	0.31
$MV, 4$	0.00***	0.87***	-0.08***	0.00	-0.02	0.89	-0.08	6.51***	14.91	0.44
MV, L	0.00	0.93***	-0.06**	0.00	-0.01	0.80	-0.25	4.67*	16.78	0.28
$HLMV$	0.00	0.34***	0.22***	-0.02	0.06	0.18	0.57	1.46	15.23	0.10
$HLEW$	0.00	0.08**	0.15***	-0.03	0.06	0.05	0.64	0.31	12.05	0.03
FMB	0.00	0.25***	0.43***	-0.05	0.07	0.18	1.00	1.54	19.25	0.08
				Default Spread mimicking portfolios						
MV, H	0.00*	0.96***	0.08***	0.00	0.02	0.87	0.22	6.67***	16.70	0.40
$MV, 2$	0.00**	0.90***	-0.05***	-0.01	-0.04**	0.93	0.05	5.95***	15.04	0.40
$MV, 3$	0.00	0.99***	-0.06***	0.02	-0.04***	0.93	-0.05	5.52**	16.50	0.33
$MV, 4$	0.00	1.09***	0.03	0.02	0.01	0.87	-0.15	4.47	18.79	0.24
MV, L	0.00	1.31***	0.09***	-0.05*	0.05**	0.82	-0.36	4.82	23.32	0.21
$HLMV$	0.00*	-0.34***	-0.01	0.05*	-0.03	0.17	0.58	1.86	13.21	0.14
$HLEW$	0.00	-0.18***	0.01	0.02	-0.02	0.09	0.61	-3.15**	9.70	-0.33
FMB	0.00*	-0.23***	0.03	0.07	-0.01	0.05	1.00	-5.28**	15.93	-0.33
				Term Spread mimicking portfolios						
MV, H	0.00	1.13***	0.23***	0.04	0.08***	0.79	0.45	7.11**	20.86	0.34
$MV, 2$	0.00	1.08***	0.14***	-0.01	0.06***	0.86	0.22	6.39**	19.00	0.34
$MV, 3$	0.00	0.99***	0.05**	0.01	0.01	0.92	0.10	5.09**	16.69	0.30
$MV, 4$	0.00	0.93***	-0.05***	0.00	-0.02*	0.93	-0.02	4.88**	15.50	0.31
MV, L	0.00	1.00***	-0.10***	-0.01	-0.05**	0.87	-0.18	4.41*	17.42	0.25
$HLMV$	0.00	0.12**	0.33***	0.04	0.13***	0.17	0.63	2.70	14.62	0.18
$HLEW$	0.00***	0.04	0.16***	0.04*	0.07**	0.09	0.69	4.11***	9.46	0.43
FMB	0.00***	-0.08	0.08	0.11**	0.11**	0.05	1.00	5.49***	13.65	0.40

Table C continued

Panel B: Pre-ranking portfolio characteristics

	Size	Book-to-Market	Momentum	HH	Turnover
		Dividend Yield mimicking portfolios			
$HLMV$	-4.20	0.02	6.43	0.073	2.783
$HLEW$	-0.86**	0.10**	1.85	0.004	2.963
FMB	-1.20**	0.12	6.10	0.015	2.251
		Default Spread mimicking portfolios			
$HLMV$	12.78***	-0.04	-4.81	0.056	2.353
$HLEW$	0.97***	-0.22***	1.94	0.004	2.778
FMB	1.36***	-0.40***	2.89	0.016	2.274
		Term Spread mimicking portfolios			
$HLMV$	-29.49***	0.24***	10.44***	0.053	2.335
$HLEW$	-1.91***	0.16***	1.84	0.004	2.734
FMB	-1.67***	0.28***	1.68	0.015	2.211

Table D: Predicting macroeconomic activity with alternative state variables at the monthly frequency

This table is the equivalent of Table III, but presents multiple regressions of macroeconomic activity (measured either with Industrial Production growth (IP) or the Chicago Fed National Activity Index (CF)) on the alternative sets of state variables at the monthly frequency. Model (1) replaces TS with RF. Model (2) includes RF (orthogonalized from TS) next to DY, DS and TS. Model (3) uses the state variables of Campbell and Vuolteenaho (2004): TS, PE and VS. Model (4) uses the state variables of Koijen et al. (2013): CP and LVL. (See Section II for a description of the variables.) I consider three horizons $S = 1, 12, 24$. *, ** and *** indicate significance at the 10%, 5% and 1%-level, respectively, using the more conservative Hansen and Hodrick (1980) asymptotic standard errors with S lags.

$$y_{t,t+S} = b_S' z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

	S	$b_{DY,S}$	$b_{DS,S}$	$b_{TS,S}$	$b_{RF,S}$ / $b_{RF\|TS,S}$	$b_{PE,S}$	$b_{VS,S}$	$b_{CP,S}$	$b_{LVL,S}$	R^2
					(1) $z_t = (DY_t, DS_t, RF_t)'$					
IP	1	0.02	-0.31***		-0.02					0.09
	12	0.29*	-0.15		-0.43***					0.12
	24	0.52**	-0.11		-0.60***					0.22
CF	1	0.10	-0.46***		0.04					0.17
	12	0.36*	-0.26		-0.33*					0.08
	24	0.54***	-0.14		-0.49**					0.14
					(2) $z_t = (DY_t, DS_t, TS_t, RF_t\|TS_t)'$					
IP	1	0.00	-0.41***	0.14***	0.15**					0.12
	12	0.27*	-0.26	0.42***	-0.16					0.15
	24	0.49**	-0.23	0.55***	-0.29					0.26
CF	1	0.02	-0.54***	0.13**	0.25***					0.22
	12	0.25	-0.36*	0.39***	0.04					0.16
	24	0.41**	-0.27	0.55***	-0.02					0.27
					(3) Campbell and Vuolteenaho (2004): $z_t = (TS_t, PE_t, VS_t)'$					
IP	1			0.07		0.16**	-0.12**			0.02
	12			0.31**		0.08	-0.10			0.09
	24			0.37***		-0.09	0.04			0.14
CF	1			0.09		0.19**	-0.31***			0.07
	12			0.35***		0.05	-0.30***			0.14
	24			0.47***		-0.16	-0.15			0.23
					(4) Koijen et al. (2013): $z_t = (CP_t, LVL_t)'$					
IP	1							0.06	-0.07	0.01
	12							0.21**	-0.22	0.08
	24							0.36***	-0.23	0.16
CF	1							0.08	0.03	0.01
	12							0.26***	-0.05	0.06
	24							0.46***	-0.03	0.21

Table E: Mimicking portfolios for alternative state variables at the monthly frequency

This table presents the three mimicking portfolios (FMB, $HLMV$ and $HLEW$) for each of the alternative state variables at the monthly frequency. Panel A presents results for the model where $z_t = (DY_t, DS_t, RF_t)'$; Panel B for $z_t = (TS_t, PE_t, VS_t)'$ as in Campbell and Vuolteenaho (2004); and, Panel C for $z_t = (CP_t, LVL_t)'$ as in Koijen et al. (2013). Focusing solely on the mimicking portfolios the alternative state variables (RF, PE, VS, CP and LVL), I report (i) post-ranking exposures $(\beta_m, \delta')'$ from the model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta' \varepsilon_{z_t}^{Full} + u_t$, (where standard errors are Newey-West with lag length one) and (ii) annualized performance (average return, standard deviation and Sharpe ratio). *, ** and *** indicate significance at the 10, 5 and 1%- level, respectively.

Panel A: $z_t = (DY_t, DS_t, RF_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{DY_t}^{Full}, \varepsilon_{DS_t}^{Full}, \varepsilon_{RF_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{DY}	δ_{DS}	δ_{RF}	R^2	ret.	dev.	ratio
RF mimicking portfolios									
HLMV	0.00	0.12***	-0.05	-0.07*	0.10**	0.04	-0.91	13.50	-0.07
HLEW	0.00**	0.06*	-0.03	-0.04	0.06**	0.03	-2.81**	9.29	-0.30
FMB	0.00*	0.11*	-0.03	-0.06	0.19***	0.06	-3.28	15.07	-0.22

Panel B: Campbell and Vuolteenaho (2004): $z_t = (TS_t, PE_t, VS_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{TS_t}^{Full}, \varepsilon_{PE_t}^{Full}, \varepsilon_{VS_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{TS}	δ_{PE}	δ_{VS}	R^2	ret.	dev.	ratio
PE mimicking portfolios									
HLMV	0.00	0.06	-0.01	0.04	-0.03	0.01	1.00	10.42	0.10
HLEW	0.00	0.07**	-0.02	0.06***	-0.04	0.04	1.06	8.04	0.13
FMB	0.00	0.03	-0.05	0.13***	-0.05	0.02	2.99	13.28	0.23
VS mimicking portfolios									
HLMV	0.00**	0.37***	-0.05	-0.05	0.33***	0.22	-3.59	17.17	-0.21
HLEW	-0.01***	0.25***	0.01	-0.05	0.27***	0.16	-5.11**	14.74	-0.35
FMB	-0.01***	0.19***	-0.02	-0.06	0.29***	0.11	-8.63***	16.77	-0.51

Panel C: Koijen et al. (2013): $z_t = (CP_t, LVL_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{CP_t}^{Full}, \varepsilon_{LVL_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{CP}	δ_{LVL}		R^2	ret.	dev.	ratio
CP mimicking portfolios									
HLMV	0.00	0.20***	0.05**	0.07**		0.09	3.08*	11.69	0.26
HLEW	0.00**	0.04	0.02	0.03		0.00	3.00**	9.16	0.33
FMB	0.00***	-0.04	0.07	0.01		0.00	5.85***	14.82	0.39
LVL mimicking portfolios									
HLMV	0.00	0.48***	-0.02	0.23***		0.25	-0.68	17.05	-0.04
HLEW	0.00	0.29***	0.01	0.14***		0.16	-0.04	12.84	0.00
FMB	0.00	0.31***	0.01	0.32***		0.19	1.07	16.48	0.06