State variable hedging and individual stocks: New evidence for the ICAPM*

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ABSTRACT

I construct a range of individual stock-based mimicking portfolios for innovations in three variables that describe investment opportunities: Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). I find that each risk factor can be hedged well out-of-sample. DY risk is not priced, whereas DS and TS risk are priced at -4.5% and +5.5%, respectively, for the average mimicking portfolio. The DS risk premium is realized in recessions alone and is a Size effect. The TS risk premium is stable and separate from the Fama and French (1993) factors and characteristics. This evidence is consistent with the Intertemporal CAPM of Merton (1973), and adds to existing portfolio-level evidence that is (i) largely silent on how to hedge and (ii) mixed and inconclusive on the issue of pricing.

JEL Classification Codes: G11, G12, G13

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This paper tests the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) among individual stocks and is the first to show that state variable risk can be hedged well out-of-sample. Moreover, the state variable risk premiums I estimate are an important addition to existing portfolio-level estimates, which are mixed and inconclusive.[1] Recent literature suggests that such conflicting evidence is perhaps unsurprising. Ahn et al. (2009), Lewellen et al. (2010) and Maio and Santa-Clara (2012) show that inferences from asset pricing tests depend critically on the chosen set of test portfolios, whereas Ang et al. (2011) argue that portfolio-level tests are inefficient relative to firm-level tests. In addition, having focused almost exclusively on the issue of pricing, the literature offers little guidance to investors who desire to hedge time-varying investment opportunities in real-time.

The ICAPM is a natural candidate to study the cross-section of stock returns given mounting empirical evidence on stochastic variation in the investment opportunity set.[2] In the ICAPM, exposure to state variables that predict this set are priced in addition to market beta. I adopt the framework of Campbell (1996), but use individual stocks to construct mimicking portfolios for Vector Auto-Regressive (VAR) innovations in three variables commonly used to predict investment opportunities in various asset classes: Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). In this way, I provide novel evidence on both hedging and pricing in the ICAPM.[3]

First, a standard deviation increase in the DY, DS and TS innovation increases the quarterly return of the typical mimicking portfolio by 1% to 3%. This out-of-sample hedging ability is a prerequisite for the mimicking portfolios to capture a risk premium in the ICAPM. Indeed, DS and TS risk are priced at an annualized premium that averages -

[1] A long history of papers test whether ICAPM-motivated 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 Maio and Santa-Clara (2012).

[2] Classic examples of predictability include Keim and Stambaugh (1986) and Fama and French (1989) - stocks and bonds; Campbell (1996) - human capital; and, Liu and Mei (1992) - real estate. Recent examples include Cochrane and Piazzesi (2005) and Ludvigson and Ng (2007, 2009) - stocks and bonds; and, Hong and Yogo (2012) - commodities. Maio and Santa-Clara (2012) predict both return and volatility in the stock market.

[3] Note, having measured 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).

4.5% and +5.5%, respectively, over the various mimicking portfolios. These estimates are consistent with the interpretation of an increasing DS as bad news and an increasing TS as good news. DY risk is not priced, however, which is likely an artefact of the VAR. Third, the DS risk premium is realized in recessions alone and is a Size effect, because it is eradicated largely in the Fama and French (1993) model (FF3M) in time-series regressions and upon the inclusion of characteristics, principally Size, in cross-sectional regressions. The TS risk premium is stable over the business cycle and separate.

I use individual stocks not only to avoid the aforementioned problems with portfolios, but also because this cross-section is more heterogeneous in exposures, which is attractive for hedging. Although it may be more natural to hedge DS and TS using bonds, the literature has focused on the stock market instead. The motivation is that the stock-based hedge portfolio is priced when alternative hedges are imperfect or when the markets are segmented. I construct mimicking portfolios in response to Hou and Kimmel (2009), who advise to report risk premiums for both a factor and its projection on the return space if the factor is non-traded and potentially unspanned. However, the maximum correlation portfolio of Breeden et al. (1989) 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 (see, e.g., Lewellen et al. (2010)). Therefore, the mimicking portfolios use a range of common strategies that weight stocks as a function of their ex ante exposures. I use these exposures to run cross-sectional regressions, as well.

As in, for instance, Petkova (2006) and Brandt and Wang (2010), the state variable risk premiums are estimated without intertemporal restrictions, which rely on observing the aggregate wealth portfolio. The motivation is that this portfolio is unobserved and the typical proxy, the CRSP value-weighted stock market return, is likely far from perfect (Roll (1977)). In addition, the state variables are known to relate importantly to many aspects of the opportunity set that need not all be traded (Cochrane (2001)). Nevertheless, I argue that the estimates are consistent with ICAPM economics, which alleviates concerns about "factor fishing" in Fama (1991), Black (1993) and Maio and Santa-Clara (2012).

First, the absence of a DY risk premium is consistent with Campbell (1996) and follows from a large negative correlation between the contemporaneous stock market return and both innovations in DY and innovations in the long-run expected return from the VAR-system. Consequently, DY is redundant, because it is included primarily for its role in predicting the stock market, whereas market beta is enough to capture both market risk and this aspect of intertemporal risk.

This argument need not imply that DS and TS are redundant, as well. 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)). Second, Fama and French (1989) argue that TS captures a term premium that is common to long maturity assets. Indeed, Campbell (1996) finds that TS also predicts human capital returns. Third, an increase in TS (steepening of the yield curve) predicts an increase in economic activity, whereas a yield curve inversion has preceded all US recessions since the 50s (see, e.g., Estrella and Hardouvelis (1991) and Adrian and Estrella (2008)). Thus, a negative price for DS risk is consistent with the simple intuition that an increasing default spread is bad news. Given that defaults cluster in recessions, it is natural that the risk premium is largest in these periods. In contrast, an increasing TS is good news.

This study contributes to three strands of the literature. First, previous work on the ICAPM has typically ignored the question of how to hedge in real-time, by running cross-sectional tests using in-sample betas. Notable exceptions are Petkova (2006) and Hahn and Lee (2006), who find that SMB and HML hedge state variables similar to the ones I analyze, ex post. In fact, SMB is a particularly natural hedge, as Baker and Wurgler (2012) interpret this return as the spread between "speculative" and "bond-like" stocks. This paper is different and sets out to construct portfolios that are maximally exposed ex ante, which is more informative for institutional investors that desire to tilt their equity portfolio towards or away from these risks. Ex ante, the mimicking portfolios load on stocks with distinct Size and Book-to-Market characteristics and are not costly to trade. Ex post, the individual stock-based mimicking portfolios hedge at least as well as SMB, HML and alternative portfolio-based mimicking portfolios in the spirit of Breeden et al. (1989) and Lamont (2001). Also, these mimicking portfolios hedge well relative to similar individual stock-based mimicking portfolios for non-traded factors in Chan et al. (1998), Pastor and Stambaugh (2003) and Ang et al. (2012).

Second, existing portfolio-level evidence on pricing is sensitive to the choice of test assets and generally inconsistent with the ICAPM (Maio and Santa-Clara (2012)). An incomplete list of papers that examine state variables similar to the ones I analyze, includes Campbell (1996), Petkova (2006) and Hahn and Lee (2006).[4] In the most popular set of test assets, 25 Size and Book-to-Market portfolios, DY and DS are not priced, whereas TS and RF (the Risk Free rate) are priced. I exclude RF, because these exposures correlate strongly with TS exposures in the cross-section. More importantly, using the now preferred set of test assets, I confirm that TS risk captures a positive premium and reveal that DS risk captures a procyclical, negative premium.

A recent, closely related paper is Cederburg (2011), who performs a firm-level test of an ICAPM including shocks to the market risk premium and the real interest rate, similar to Brennan et al. (2004). He concludes that the ICAPM outperforms the CAPM, although the intertemporal risk prices are typically insignificant. This paper differs in three dimensions. First, I estimate betas out-of-sample, which is more informative for hedging. Second, I estimate significant risk prices for the most popular state variables in the literature. Third, I provide additional information by comparing different mimicking portfolios, recessions versus expansions and a quarterly and monthly frequency.

Finally, these results add 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. (2011). For instance, results in Petkova (2006) and Hahn and Lee (2006) suggest that SMB and HML can substitute for my state variables in portfolio-level tests. In cross-sectional regressions for individual stocks, I confirm evidence to the contrary in Cederburg (2011)

[4] Kan et al. (2012) find that Petkova's model (including VAR-innovations in DY, DS, TS and RF) performs impressively in R^2 compared to seven popular asset pricing models among various sets of portfolios.

and Maio and Santa-Clara (2012). To be precise, I find that exposures to SMB and DS are priced largely because these exposures correlate with Size. This finding 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 market conditions. Although, HML and TS are correlated to some extent as well, it is only HML that is eradicated by the inclusion of Book-to-Market in these cross-sectional regressions.

The rest of this paper is organized as follows. Section I presents the ICAPM framework, data and methodology. Section II tests whether mimicking portfolios in fact mimick. Section III estimates risk premiums. Section IV confronts the ICAPM factors with the Fama and French (1993) factors and characteristics. Section V presents a number of robustness checks. Section VI summarizes and concludes.

I ICAPM state variable mimicking portfolios

This section describes the ICAPM framework, data and methodology used to construct state variable mimicking portfolios. To fix ideas, the ICAPM can be approximated in discrete time, leading to the pricing equation:

$$E_{t-1}\left(r_{i,t}\right) = \lambda_{m,t-1}\beta_{i,m,t-1} + \sum_{k} \lambda_{k,t-1}\delta_{i,k,t-1}, \tag{1}$$

where $E_{t-1}\left(r_{i,t}\right)$ is the expected excess return ($r_{i,t} = R_{i,t} - R_{f,t}$) of asset i, $\lambda_{m,t-1}$ is the market risk premium, and $\lambda_{k,t-1}$ is the price of risk for state variable k (all conditional on the information set at $t-1$). The exposures $\beta_{i,m,t-1}$ and $\delta_{i,t-1}$ are the slope coefficients from the return-generating process $r_{i,t} = \alpha_{i,t-1} + \beta_{i,m,t-1}r_{m,t} + \delta'_{i,t-1}\varepsilon_t + \nu_{i,t}$, where ε_t is a vector containing innovations in the relevant state variables.

To be precise, $\lambda_{m,t-1}$ is a function of the coefficient of relative risk aversion of the representative agent, which is time-varying (see, e.g., Campbell and Cochrane (1999)). In turn, $\lambda_{k,t-1}$ is a function of the derivative of the indirect marginal utility of wealth with respect to state variable k and may also vary over time as in Ferson and Harvey (1991), consistent with time-varying predictability.[5] When the innovations in the state variables are orthogonal to the market (the empirically relevant case), $\lambda_{m,t-1}$ is positive.[6] When the innovations are also orthogonal to each other, $\lambda_{k,t-1}$ is negative (positive) if an increase in the state variable is bad (good) news for the agent and increases (decreases) his marginal utility of wealth.

Note, estimating equation (1) using conditional exposures ($\beta_{i,m,t-1}$ and $\delta_{i,t-1}$) for individual stocks (i) is novel in the context of the ICAPM. Indeed, previous literature has focused on the issue of pricing, typically by running cross-sectional regressions with full sample betas for a small set of portfolios. First, conditional exposures, estimated using historical data only, ensure that the investor can apply and could have applied these strategies in real-time. Second, the use of individual stocks provides the investor with the broadest possible range of exposures and allows me to estimate risk premiums more efficiently.

A State variables

I focus on three state variables known to predict returns in various asset classes: the Dividend Yield (DY) of the CRSP value-weighted stock portfolio (dividends over the last 12 months divided by 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). Data on bond yields are from the FRED® database of the Federal Reserve Bank of St. Louis. Note, in a number of previous applications (e.g., Petkova (2006) and Kan et al. (2012)) the Risk-Free rate (RF) is included as fourth state variable. In a robustness check (Section V.A), I find that RF is largely redundant in the presence of TS

[5] For instance, Rapach et al. (2010), Henkel et al. (2011) and Dangl and Halling (2012) provide evidence for time-varying predictability in stock markets; and, Ang et al. (2008) for bond markets, as a result of monetary policy regimes.

[6] To be precise, $\begin{pmatrix} \lambda_{m,t-1} \\ \lambda_{t-1} \end{pmatrix} = \Sigma_{m\varepsilon,t-1} \begin{pmatrix} \gamma_{m,t-1} \\ \gamma_{t-1} \end{pmatrix}$, where $\Sigma_{m\varepsilon,t-1}$ is the conditional covariance matrix of the market and the innovations in the state variables. Here, $\gamma_{m,t-1}$ is the coefficient of relative risk aversion $(-WJ_{WW}/J_W)$ and $\gamma_{k,t-1}$ is $(-J_{WF_k}/J_W)$, where $J(W(t), F(t), t)$ is the indirect utility of wealth $(W(t))$ of the representative agent and $F(t)$ is the vector with levels of the state variables, with subscripts denoting partial derivatives at $t-1$.

and I therefore exclude it.

I adopt the Vector Auto-Regressive (VAR) approach of Campbell (1996) and assume the state variables follow a $VAR(1)$-process. To be consistent with previous work, I also include the CRSP value-weighted stock market return, such that $z_t = (r_{m,t}, DY_t, DS_t, TS_t)'$. However, given that $r_{m,t}$ is likely a poor proxy for the return on aggregate wealth, I will not put intertemporal restrictions on the risk prices. Furthermore, t indexes either quarter-end or month-end, depending on the sampling frequency. I consider two frequencies to alleviate concerns about data-mining and potential horizon-effects in the relation between the state variables and the investment opportunity set. Moreover, this is an important consideration because the investment horizon of the representative agent is unknown (see, e.g., Kothari et al. (1995), Campbell (1996) and Brennan and Zhang (2012)). To ensure the exercise is fully conditional, I run the VAR using only historical data at the end of each period $t-1$, such that $z_\tau = A_0^{t-1} + A_1^{t-1} z_{\tau-1} + e_\tau^{t-1}$. Here, the superscript $t-1$ indicates the length of the sample and $\tau = 1, .., t-1$. Following Petkova (2006), the innovations e_τ^{t-1} are orthogonalized from $r_{m,\tau}^{t-1}$ and scaled to have the same variance as $r_{m,\tau}^{t-1}$. This orthogonalization is particularly important for DY, because the correlation between the excess market return and the innovation in DY that is not orthogonalized is -0.89 at both frequencies. The transformed innovations in the state variables, used as risk factors in the asset pricing model, are denoted $\varepsilon_\tau^{t-1} = (\varepsilon_{DY_\tau}^{t-1}, \varepsilon_{DS_\tau}^{t-1}, \varepsilon_{TS_\tau}^{t-1})'$.[7] Note, the innovations are not orthogonalized from each other, because (i) their correlations are all below 0.20 and (ii) this could add additional noise through the arbitrary ordering of the variables.

B Mimicking portfolios

To find out whether I can identify stocks that are exposed to the innovations ε_t and if these exposures are priced, I form out-of-sample mimicking portfolios at $t-1$ with weights that are a function of historical betas. I use all ordinary common stocks traded on NYSE, AMEX

[7] The results are similar when I use innovations from a full-sample VAR. This approach is common in previous work, but uses forward-looking information. Further, the results are qualitatively similar for innovations from a $VAR(2)$ and for first-differences in the state variables. These results are available on request.

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 alter the main results. Furthermore, I require that at least four out of the last five years of returns are available for a stock to be included. The sample period is April 1962 to December 2010. This sample start is often used in empirical work and coincides with the introduction of AMEX stocks in the CRSP file and the availability of daily treasury rate data. Accounting for a burn-in period of five years, this sample amounts to a total of 175 quarterly and 525 monthly post-ranking returns.

B.1 Exposures

I estimate betas using a weighted least-squares regression over all observations $\tau = 1, ..., t-1$ and shrink these betas as suggested in Vasicek (1973). These modifications to the usual rolling-window beta are important, because exposures to non-traded and macroeconomic factors tend to be small and hard-to-estimate (see, e.g., Duarte (2010)).[8] First, 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. To be precise, for each stock $i = 1, ..., N_{t-1}$ the WLS-estimator of $\delta_{i,t-1}$ is given by

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

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 of $\widehat{\delta_{i,k,t-1}}$ for $k = DY, DS, TS$:

$$\widehat{\delta_{i,k,t-1}^{v}} = \widehat{\delta_{i,k,t-1}} + \frac{var_{TS}(\widehat{\delta_{i,k,t-1}})}{\left[var_{TS}(\widehat{\delta_{i,k,t-1}}) + var_{CS}(\widehat{\delta_{i,k,t-1}})\right]} \left[mean_{CS}(\widehat{\delta_{i,k,t-1}}) - \widehat{\delta_{i,k,t-1}}\right], \tag{3}$$

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

where the subscripts TS and CS denote means and variances taken over the time-series dimension τ and cross-sectional dimension i, respectively. In this way, $\widehat{\delta^v_{i,k,t-1}}$ 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. (2010) show that this adjustment can improve forecasts of ex post exposures. From this point forward, all results are based on the Vasicek-adjusted exposures $\widehat{\delta^v_{i,k,t-1}}$, simply denoted $\delta_{i,k,t-1}$.

B.2 Mimicking portfolio weights

In theory, one can find the maximum correlation mimicking portfolio, with mean return equal to the factor risk premium, by regressing the factor on the cross-section of asset returns, or equivalently a set of spanning assets (see, e.g., Breeden et al. (1989) and Hou and Kimmel (2009)). However, we cannot run this regression for the cross-section of individual stocks, because the cross-sectional dimension is larger than the time-series dimension. Moreover, Lewellen et al. (2010) argue that many cross-sectional asset pricing tests in the past are flawed by having estimated risk premiums in a small set of portfolios that likely do not span the entire cross-section. Therefore, I use individual stocks to construct the mimicking portfolios, but use a range of alternative weighting schemes. Thus, I construct mimicking portfolios of the form $r^{mp}_{k,t} = w'_{k,t-1}(\delta_{k,t-1})r_t$ for each factor k. These portfolios can be thought of as simple, out-of-sample proxies for the maximum correlation portfolio and are consistent with asset pricing model in equation (1).

I differentiate between weighting schemes that assign a weight to only a fraction of the available stocks and those that assign a weight to all stocks. For the first, arguably the most interesting from a practical point of view, I sort stocks at the quintiles of ranked exposures and construct market value-weighted and equal-weighted portfolios. I focus, in particular, on the High minus Low (HML) spreading portfolios.

For the last, I consider two alternatives. The first, w_{beta}, is suggested by Lehmann

(1990) and defines the mimicking portfolio weights for factor k as

$$w^{beta}_{i,k,t-1} = \frac{\delta_{i,k,t-1} - \overline{\delta_{k,t-1}}}{\sum_{i:\delta_{i,k,t-1}-\overline{\delta_{k,t-1}}>0} \delta_{i,k,t-1} - \overline{\delta_{k,t-1}}}, \tag{4}$$

where $\overline{\delta_{k,t-1}}$ is the cross-sectional average exposure. This strategy places an aggregate bet of one dollar long (short) on those stocks with above (below) average exposures, with the absolute weight increasing in distance from the average.

The second, w_{FMB}, is based on the Fama and MacBeth (1973) cross-sectional regression. Fama (1976) shows that the estimated risk premium in this procedure is the return on a zero-investment portfolio that has a beta of one with respect to the factor of interest and a beta of zero with respect to the other factors. Thus, in an ex ante sense, this mimicking strategy is ideal for the purpose of this paper. However, in the context of the ICAPM, this time series perspective on the cross-sectional regression is novel.

To be precise, the weight on each stock at time $t-1$ in case factor k is given by the $(k+1, i)$-th entry of the $(k+1) \times N_{t-1}$ matrix given by

$$(B'_{t-1}B_{t-1})^{-1}B'_{t-1}, \text{ for } B_{t-1} \text{ with typical row } B_{i,t-1} = [1, \beta_{i,m,t-1}, \delta'_{i,t-1}]. \tag{5}$$

Because $B_{i,t-1}$ contains pre-ranking betas, which are noisy, one can expect the post-ranking exposure to the state variable of interest to be smaller than one and to the other factors unequal to zero. Indeed, testing whether the post-ranking exposures are both statistically and economically significant is an important reality check of the procedure that applies for all mimicking strategies.

II Do mimicking portfolios in fact mimick?

This section tests whether each mimicking portfolio succeeds in its primary objective, that is, being exposed to the risk factor it is supposed to mimick. An ex post exposure means that the portfolios can be used to hedge in practice. Moreover, this exposure is a prerequisite for the mimicking portfolios to capture a risk premium in the ICAPM and suggests the state variables are not useless, in the sense of Kan and Zhang (1999) and Kleibergen (2010). Furthermore, I analyze whether the portfolios are costly to trade and whether they load on stocks with certain characteristics.

A Post-ranking exposures

Table I presents post-ranking exposures $(\beta_m, \delta')'$ from the four-factor model $r^{mp}_{k,t} = \alpha + \beta_m r_{m,t} + \delta'[\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t}]' + u_t$. In this case, the innovations ε^{Full}_t are constructed by running the $VAR(1)$ over the full sample. To accomodate interpretation, the innovations are orthogonalized from $r_{m,t}$ and scaled to have the same variance as $r_{m,t}$. I present exposures for the mimicking portfolios ($HML_{MVW}, HML_{EW}, w_{beta}$ and w_{FMB}) as well as the market value-weighted quintile portfolios for each factor $k = DY, DS, TS$ in Panel A to C. The main results, that is, for the quarterly frequency are presented in columns one to five. Columns six to ten present results for the monthly frequency as a check of robustness.

Insert Table I about here.

At the quarterly frequency, the post-ranking exposures to the relevant innovations are large and significant for all mimicking portfolios. In Panel A, loadings on $\varepsilon^{Full}_{DY_t}$ range from 0.11 ($p < 0.10$) for w_{beta}, to 0.25 and 0.29 ($p < 0.01$) for HML_{MVW} and w_{FMB} , respectively. In Panel B, loadings on $\varepsilon^{Full}_{DS_t}$ range from about 0.10 ($p < 0.10$) for HML_{MVW}, HML_{EW} and w_{beta}, to 0.31 ($p < 0.05$) for w_{FMB}. In Panel C, loadings on $\varepsilon^{Full}_{TS_t}$ range from 0.09 ($p < 0.05$) for w_{beta}, to 0.15 ($p < 0.01$) and 0.18 ($p < 0.05$) for HML_{MVW} and w_{FMB}, respectively. Further, in each panel, we see a roughly decreasing pattern moving from High to Low among the single-sorted portfolios. Finally, the typical mimicking portfolio is only exposed to the one ICAPM factor it is supposed to mimick. Although, DY and DS mimicking portfolios load strongly on MKT.

At the monthly frequency, we see that DY mimicking portfolios perform slightly better, whereas TS mimicking portfolios perform slightly worse. In contrast, DS mimicking portfolios perform much worse, given that exposures to $\varepsilon_{DS_t}^{Full}$ are small and insignificant ranging from 0.00 for w_{beta} to 0.06 for w_{FMB}. Evidently, we cannot identify stocks ex ante that hedge DS risk at this frequency.[9]

It is important to note that the out-of-sample nature of these strategies comes at the cost of not predicting betas perfectly. This problem is immediately clear for w_{FMB}, which has a pre-ranking beta that equals one by construction. At the quarterly frequency, the post-ranking betas fall to 0.29, 0.31 and 0.18 in case of DY, DS and TS, respectively. Nevertheless, these exposures represent a meaningful hedge and translate to quarterly returns ranging from about 1.6% to 2.7% when the risk factors increase by one standard deviation. As a benchmark, these hedge returns are larger than for individual stock-based mimicking portfolios of liquidity and inflation in Pastor and Stambaugh (2003) and Ang et al. (2012).

Moreover, these exposures are at worst similar to two alternative hedges. First, Panel D presents exposures for the Fama and French (1993) factors, which have been found to load on similar state variables ex post (Petkova (2006) and Hahn and Lee (2006)). We see that SMB only loads marginally on $\varepsilon_{DY_t}^{Full}$ at 0.07, whereas HML loads significantly on $\varepsilon_{DS_t}^{Full}$ and $\varepsilon_{TS_t}^{Full}$ at -0.17 and 0.16, respectively. Second, Panel E presents exposures for portfolio-based mimicking portfolios in the spirit of Breeden et al. (1989). These strategies use as base assets 25 Size and Book-to-Market portfolios instead of individual stocks in an otherwise identical out-of-sample sort into quintiles.[10] Among these mimicking portfolios, only the one for TS loads significantly on $\varepsilon_{TS_t}^{Full}$ at 0.11 ($p < 0.01$). At the monthly frequency, the exposures to $\varepsilon_{DY_t}^{Full}$ and $\varepsilon_{TS_t}^{Full}$ are similar, but neither alternative hedge loads on $\varepsilon_{DS_t}^{Full}$.

I conclude that state variable risk can be hedged well out-of-sample, except for DS risk at the monthly frequency. Moreover, the individual stock-based mimicking portfolios are "as good as it gets" for an investor that desires to hedge in the stock market. Thus, these strategies are an important step forward in using information from the cross-section of individual stocks in real-time. Although, HML is second-best in hedging TS risk at

[9] Note however, Section III shows that the returns for DS mimicking portfolios are quite similar at both frequencies. A potential explanation is that the monthly DS mimicking portfolios are marginally exposed to quarterly DS innovations when their returns are compounded.

[10] The conclusions are largely unaltered when I use instead 30 industry portfolios as base assets.

both frequencies, the results below show that the risk premiums for HML and TS differ in important dimensions.

B Pre-ranking characteristics

Table II is structured similarly to Table I and describes the mimicking portfolios in terms of various characteristics (averaged over time). In each period, Pre-ranking exposure, Size (\$ billion), Book-to-Market and Momentum are weighted cross-sectional averages, whereas Turnover (annualized) is the amount of trading required to rebalance.[11] For HML_{MVW}, HML_{EW} and w_{beta}, Turnover is calculated as

$$\frac{\sum_i \left| w_{i,t-1} \left(\frac{1}{2} \sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right| \right) - w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}{\sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}. \tag{6}$$

The numerator sums all absolute changes in the portfolio weights from the instant before rebalancing, $w_{i,t-2}\left(1 + r_{i,t-1}\right)$, to the instant after, $w_{i,t-1}$, where the latter is scaled to allow the long and short position to grow equally over time from the initial value of one dollar each. The denominator scales by the size of the portfolio.

For w_{FMB}, the total long and short position do not equal one dollar and vary over time. Therefore, Turnover is calculated as

$$\frac{\sum_i \left| w_{i,t-1} - w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}{\sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}, \tag{7}$$

such that you trade to keep the pre-ranking beta exactly equal to one.

Insert Table II about here.

[11] 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.

First, we see that there is a wide spectrum of exposures to DY, DS and TS in the cross-section of individual stocks. Pre-ranking exposures are about one at the quarterly frequency and about 0.6 at the monthly frequency. Thus, sampling at the lower frequency presents a wider range of exposures, perhaps due to reduced noise in both returns and the non-traded factors. However, note that it is only in the case of DS and TS that this leads to a larger spread in post-ranking exposures in Table I, as well.

Next, I find that transaction costs are acceptable, i.e., small relative to the risk premiums analyzed in the next section. For all strategies, Turnover is about 1.5 at the quarterly frequency and about 2.5 at the monthly frequency. This figure implies that an investor, who is long and short one unit and rebalances quarterly (monthly), will trade three (five) units per year.[12] These trades add up to transaction costs of about 37.5 (62.5) basis points, assuming an average quoted half-spread of 12.5 basis points.[13]

For the characteristics Size, Book-to-Market and Momentum, let us focus on HML_{EW} at the quarterly frequency. This weighting scheme presents results that are typical and most comparable to previous work, because it equal-weights each characteristic in the top and bottom quintile.[14] First, high DY exposure stocks are smaller by -1.10$ billion and have higher book-to-market ratios by 0.13. Second, Size and Book-to-Market are also significant for DS mimicking portfolios at 0.81$ billion and -0.36, respectively. The fact that small stocks have lower exposures to DS risk is consistent with Perez-Quiros and Timmermann (2000) and Baker and Wurgler (2012). These authors argue that small firms are more vulnerable to variation in credit market conditions over the business cycle, such that an increasing DS signals lower cash flows and higher discount rates for smaller stocks. In this light, it is surprising that SMB does not load on DS risk in Table I. The negative relation between DS exposure and Book-to-Market is consistent with the negative loading of HML on DS risk in Table I and the common interpretation of high Book-to-Market as indicative

[12] Note, rebalancing the portfolios only at the end of the year rougly halves the amount of trading required, but leaves all other results largely unchanged.

[13] This estimate likely overestimates transaction costs in recent years (see, e.g., Chordia et al. (2011) and Hendershott et al. (2011)).

[14] Note, the size characteristic is extreme in case of HML_{MVW}, because this strategy implicity squares market values.

of relative distress (Fama and French (1995)). Third, high TS exposure stocks are smaller by over 1.23$ billion, whereas their Book-to-Market ratio is larger by about 0.16. Both characteristics are consistent with Petkova (2006) and Hahn and Lee (2006) and with the positive loadings of both SMB and HML on TS risk in Table I. 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 (growth) stocks are low (high) duration assets. Then, if an increasing TS signals higher expected returns on high duration assets, value will outperform growth contemporaneously.

For each state variable, I find in unreported results that the Book-to-Market characteristic is monotonically related to pre-ranking exposure. In contrast, the Size characteristic presents an inverted U-shape, consistent with the common intuition that smaller 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 and negative for DS. In the next section, I test these hypotheses and analyze the empirical relation between the characteristics and the state variable risk premiums in cross-sectional regressions.

III State variable risk premiums

Given that the mimicking portfolios allow the investor to hedge state variable risk in real-time, the ICAPM implies that the investor will pay a premium for these portfolios. Therefore, this section tests whether the estimated exposures to intertemporal risks are priced. First, I present results for the previously introduced mimicking portfolios. Subsequently, I focus attention on the risk premiums in cross-sectional regressions, both excluding and including characteristics, because the mimicking portfolios were found to load distinctively on Size and Book-to-Market.

A Unconditional risk premiums

A.1 Mimicking portfolios

Table III presents annualized average and risk-adjusted returns (i.e., CAPM, FF3M and Carhart's four-factor model (FFCM) α's), standard deviations and Sharpe ratios in the same fashion as Table I.[15]

Insert Table III about here.

Focusing on the quarterly frequency, we see that exposure to DY risk is not priced. The average return of all DY mimicking portfolios is almost zero, even though standard deviations increase with DY exposure among the single-sorted portfolios. Second, DS risk is rewarded with a negative risk premium in all weighting schemes. In case of w_{FMB}, HML_{EW} and w_{beta} the risk premium is economically large and significant at the 5%-level at -6.90%, -4.85% and -4.98% per annum, respectively. This risk premium translates to a Sharpe ratio of about 0.40, which is large relative to 0.30 for the aggregate stock market. In case of HML_{MVW}, the risk premium is insignificant at -2.07%, which is suggestive of a Size effect. In line with this suggestion, the negative risk premiums are captured largely in the FF3M, mainly due to a large negative loading on SMB. Finally, TS risk is rewarded with a consistent positive risk premium that is economically large and significant in all weighting schemes at 5.29% ($p < 0.05$) in case of HML_{MVW} and almost 5.80% ($p < 0.01$) for the remaining weighting schemes. The corresponding Sharpe ratios are large, as well, and range from 0.37 to 0.61. These risk premiums are not captured in the CAPM nor in the FF3M and FFCM, where alphas are large and typically significant ranging from 3% to 5%. Furthermore, consistent with a risk-based interpretation, we see that both standard deviation and Sharpe ratio increase with TS beta.

The main results are similar at the monthly frequency, although the annualized risk premiums for both DS and TS are less stable over the various weighting schemes.[16] First,

[15] The inclusion of the traded liquidity factor of Pastor and Stambaugh (2003) has little effect on the risk-adjusted returns.

[16] Note, the fact that the risk premiums are typically largest for w_{FMB} is consistent with the relatively large pre- and post-ranking exposures for this weighting scheme.

the DS risk premium is negative and significant at the 5%-level in case of w_{FMB}, HML_{EW} and w_{beta} ranging from -5.54% to -2.88%, but is positive and insignificant for HML_{MVW} at 2.13%. This variability is perhaps unsurprising taking into account that these portfolios are not exposed to DS risk in the first place. As before, we see that adding SMB (and HML) has a considerable impact. For TS, the risk premium is insignificant in case of HML_{MVW} at 2.84%, but is large and significant in average and risk-adjusted returns for the remaining weighting schemes.

I conclude that the risk premiums are quite robust in size and sign. Nevertheless, the observed variation is informative of where exactly the risk premium is coming from and for practitioners who might prefer one weighting scheme over another, for instance, depending on ex post hedging capacity or trading costs. We have also seen that potentially interesting patterns in the cross-section of expected returns can be missed when considering only one particular combination of weighting scheme and frequency. For instance, both DS and TS risk premiums are rather anomalous for HML_{MVW} at the monthly frequency, which is a popular combination in empirical work.

A.2 Cross-sectional regressions

Table IV presents Fama and MacBeth (1973) cross-sectional regressions for individual stocks. As argued by Litzenberger and Ramaswamy (1979) and Ang et al. (2011), firm-level tests are more efficient than portfolio-level tests, because the larger amount of information, that is, the wider dispersion in betas, more than makes up for the larger degree of noise in the estimated betas when estimating risk premiums. I use the pre-ranking exposures of the previous section as explanatory variables in the second stage.[17] In Section V.B, I show that using exposures to the traded mimicking portfolios instead gives similar risk premiums. In Panels A (quarterly) and B (monthly), I compare the performance of the four-factor ICAPM model to a model that additionally includes the three usual character-

[17] The results are similar when I use simple instead of multiple regression betas, or equivalently, a covariance-based test.

istics: Size, Book-to-Market and Momentum.[18] Berk (1995) and Jagannathan and Wang (1998) suggest that the inclusion of characteristics allows the researcher to detect model misspecification. It is important to note, however, that characteristics do not suffer from any measurement problems, which exposures do, such that the cross-sectional test is biased in their favor.[19]

Thus, in each period t, I estimate λ_t's using

$$
\begin{aligned}
r_{i,t} &= \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t-1}} + \lambda_t'\widehat{\delta_{i,t-1}} + \upsilon_{i,t} \text{ and} \qquad (8)\\
r_{i,t} &= \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t-1}} + \lambda_t'\widehat{\delta_{i,t-1}} + \lambda_{chars,t}^{'}[\text{Size}_{i,t-1},\text{BM}_{i,t-1},\text{MOM}_{i,t-1}]' + \upsilon_{i,t}. \qquad (9)
\end{aligned}
$$

The first four rows of Panels A and B present the unconditional average risk premiums, $\widehat{\lambda_{full}} = \frac{1}{T}\sum_t \widehat{\lambda}_t$, the corresponding Fama and MacBeth (1973) t-statistics, and the average cross-sectional R^2. Panel C presents select results for the FF3M as a benchmark.

Insert Table IV about here.

By construction, the risk premiums from equation (8) are identical to the average returns of the Fama-MacBeth mimicking portfolios in Table III. Thus, without characteristics, the risk premiums for DS and TS risk are large and significant at -6.90% ($t = -2.89$) and 5.71% ($t = 3.12$), respectively, whereas DY risk is not priced. Further, the MKT risk premium is positive, but small and insignificant, at 1.83%.[20] The R^2 equals 3.72%, which is low, but typical for this exercise. For instance, the R^2 for the FF3M is similar in Panel C at 4.25%. The inclusion of Size (positive), Book-to-Market (negative) and Momentum (positive) increases the fit to 6.75% and eradicates a considerable chunk of the DS risk premium, leaving a marginally significant -2.51% ($t = -1.69$). The TS risk premium is

[18] Following Chordia et al. (2011), 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.

[19] Indeed, the errors-in-variables bias introduced by using estimated exposures ($\widehat{\beta_{i,m,t-1}}$ and $\widehat{\delta_{i,t-1}}$) likely causes these regressions to *understate* the importance of intertemporal risk.

[20] Similar to what happens in portfolio-level tests, I find that the MKT risk premium is large and significant at about 7% when restricting the intercept to zero. In contrast, the ICAPM factor risk premiums are largely unaffected.

smaller as well, but remains economically large and significant at 3.61% (t = 2.63). To gauge the importance of this result, Panel C shows that both SMB (2.04%, t = 1.30) and HML (2.66%, t = 2.03) are eradicated completely when their underlying characteristics are included.

In many directions, the results are similar at the monthly frequency. The risk premiums for DS and TS are large and significant without characteristics at -5.54% ($t = -2.31$) and 5.73% (t = 2.75), respectively. Now, in the ICAPM model, the DS risk premium is eradicated completely by the inclusion of characteristics, just as SMB and HML are in the FF3M (unreported). Again, the TS risk premium stands out and remains marginally significant at 2.89% (t = 1.75). In line with previous evidence, unreported results show that the eradication of the DS risk premium is driven by the inclusion of Size at both frequencies.

A.3 Discussion

On one hand, the absence of a DY risk premium is surprising, because high DY risk stocks are (i) small and high Book-to-Market (Table II) (ii) systematically risky (Table III) and (iii) exposed to the most popular predictor of stock market returns. A possible explanation is that DY does not predict returns out-of-sample, as argued in Bossaerts and Hillion (1999), Goyal and Welch (2003) and Ang and Bekaert (2007). However, this conclusion is inconsistent with, among others, Cochrane (2008) and Binsbergen and Koijen (2010). An alternative explanation that does not take sides in this debate follows Campbell (1996) and builds on the fact that short-run movements in the dividend yield are largely driven by current stock returns. In turn, the current stock return is strongly negatively correlated with innovations in the long run expected return in the full sample VAR-system, at -0.89 and -0.86 at the quarterly and monthly frequency, respectively. As a result, assets that covary positively with the contemporaneous return tend to covary negatively with expectations of future returns, such that market beta largely incorporates the pricing implications of the VAR and DY is redundant.

This argument also suggests that DS and TS are priced for reasons other than their impact on long run expected stock returns, or in other words, that both must relate importantly to other aspects of the investment opportunity set. Indeed, neither DS nor TS is an important predictor in the VAR, consistent with a large body of evidence that casts doubt on their ability to predict (see, e.g., Bossaerts and Hillion (1999) and Guo (2006)). For instance, when $\varepsilon_{DS_t}^{Full}$ ($\varepsilon_{TS_t}^{Full}$) increases by one standard deviation, the long run expected return changes only by -0.3% (1.5%), compared to 2.5% for $\varepsilon_{DY_t}^{Full}$.[21]

However, a negative price for DS risk is consistent with the simple intuition that an increasing default spread signals worsening credit market conditions, which is bad news that increases the marginal rate of substitution. Consequently, low DS beta stocks have high returns. Furthermore, I find that this premium is largely a Size effect. First, Table II shows that low DS beta stocks tend to be small. Since low DS beta stocks are also volatile, one can consider them "speculative" in the sense of Baker and Wurgler (2012). Second, the DS risk premium is largely eradicated in the FF3M time-series regressions, mainly due to a negative loading on SMB, and by the inclusion of characteristics, principally Size, in cross-sectional regressions.

A positive price for TS risk is consistent with Fama and French (1989), who argue that an increasing TS predicts higher expected returns on *all* long term assets. Furthermore, it is consistent with the observation that a steepening slope of the yield curve predicts economic activity to increase, whereas a yield curve inversion has preceded all US recessions since the 50s, with only one false signal (see, e.g., Adrian and Estrella (2008) and Gilchrist and Zakrajsek (2012)). Hence, the marginal rate of substitution is high when TS is low (inverted) and investors will pay a premium for low beta assets.[22] In contrast to DS, the TS risk premium is largely separate from the Fama and French (1993) factors and characteristics.

[21] These impacts are calculated in an orthogonalized full sample VAR-system similar to Campbell (1996) at the quarterly frequency.

[22] Cochrane and Piazzesi (2005) find that a tent-shaped linear combination of forward rates (henceforth CP) is a better predictor of both bond and stock returns than TS. I find that the two factors are correlated (both in the time-series and cross-section), such that it is unsurprising that replacing TS with CP gives similar positive risk premiums in the cross-section of individual stocks. The results for these CP mimicking portfolios are available upon request.

Having determined the unconditional risk premiums for these VAR-factors in the cross-section of individual stocks, the now preferred set of test assets, one might wonder how these compare to previous portfolio-level estimates in e.g., Campbell (1996), Petkova (2006), Kan et al. (2012) and Maio and Santa-Clara (2012). First, I show that the absence of a DY risk premium extends to the case of individual stocks, consistent with its redundancy in the presence of the market portfolio. Second, I reveal that DS risk is rewarded with a negative premium, whereas previous estimates indicate that DS risk is not priced. Moreover, I show that this DS risk premium is largely a Size effect in an ex ante sense. This finding adds to Hahn and Lee (2006), who conclude that SMB loads on first-differences in DS, ex post. It is important to note, however, that SMB does not load on VAR-innovations in DS in Table I.

Finally, the positive TS risk premium I estimate is consistent with a positive, marginally significant estimate among 25 Size and Book-to-Market portfolios. Having said that, Maio and Santa-Clara (2012) show that the portfolio-level estimate depends critically on the choice of portfolios. For instance, among 25 Size and Momentum portfolios, the TS risk premium is estimated to be significantly negative. Furthermore, I confirm Hahn and Lee (2006) in that HML loads strongly on TS risk in Table I. However, in contrast to previous evidence, both time-series and cross-sectional regressions suggest that the TS risk premium is largely separate from the Fama and French (1993) factors and characteristics.[23] I further address the relations with SMB, HML, Size and Book-to-Market in Section IV.

B Conditional risk premiums: Business cycle variation

In this subsection I analyze whether the state variable risk premiums vary over the business cycle. Holding exposures constant, this time-variation is consistent with the ICAPM when risk aversion or the relation between the state variable and the investment opportunity, or both, vary over the business cycle. For instance, Campbell and Cochrane (1999) argue that

[23] The conclusions from time-series FF3M and FFCM regressions are largely unchanged for both DS and TS when I replace the sort-based factors SMB, HML and MOM with the time-series of cross-sectional regression risk premiums for Size, Book-to-Market and Momentum (see, also, Hoberg and Welch (2009)).

risk aversion is larger in economic downturns, whereas Henkel et al. (2011) and Dangl and Halling (2012) provide evidence for business cycle variation in stock market predictability. I use the Chicago FED National Activity Index (CFNAI) to distinguish between recessions and expansions.[24] For instance, Hong and Yogo (2012) find that CFNAI predicts returns in stock, bond and commodity markets. Following convention, a month-end CFNAI value below -0.7 signals a recession month or quarter coming up.[25] This gives 26 (77) recession and 149 (448) expansion quarters (months).

B.1 Mimicking portfolios

Table V presents annualized average returns and FF3M α's for the mimicking portfolios in each state. The inclusion of either MKT or MOM has little impact on risk-adjusted returns, consistent with the unconditional evidence.

Insert Table V about here.

At the quarterly frequency we see that the DY risk premiums (in recessions, expansions and the differences) are insignificant for all weighting schemes. In contrast, the DS risk premium is strongly procyclical.[26] In expansions, the average return for DS mimicking portfolios is small and ranges from a marginally significant -3.64% to an insignificant 0.51%. In contrast, the annualized average returns are large and significant at the 5%-level in recessions, ranging from -25.59% (for w_{FMB}) to -14.28% (for HML_{EW}). The corresponding differences are significant at the 10%-level and range from -21.95% to -11.08%. Also, we see that average returns decrease monotonically in DS exposure in recessions alone. As in the unconditional case, the FF3M typically eradicates a substantial fraction of the recession risk premium and therefore also the recession minus expansion difference.

Finally, the TS risk premium is consistently positive and economically large in both

[24] CFNAI is a weighted average of 85 indicators of U.S. economic activity and is available in real-time since 2001. I use the 3-month moving average of the index. The results are similar for NBER dating.

[25] I lag the index by an extra month, to account fully for a reporting delay of about three to four weeks.

[26] It is important to note that neither ex ante nor ex post DS exposures are larger in recessions.

states of the world, ranging from 4.96% to 6.29% in expansions and from 2.40% to 7.20% in recessions. Due to the limited size of the recession sample, only the expansion risk premiums are significant. These risk premiums are quite robust to the inclusion of SMB and HML. In expansions, α_{FF3M} is large and significant at about 5%. In recessions, α_{FF3M} is also large, but insignificant ranging from 1.98% to 4.63%. These conclusions hold up well at the monthly frequency, although the DS and TS risk premiums vary a bit more over the various weighting schemes, which is again similar to the unconditional case.

B.2 Cross-sectional regressions

The last twelve rows of Panel A and B l in Table IV present the average risk premium in CFNAI expansions and recessions, i.e., $\widehat{\lambda_{Exp}} = \frac{1}{T_{Exp}} \sum_{t:CFNAI_{t-1} > -0.7} \widehat{\lambda}_t$ and $\widehat{\lambda_{Rec}} = \frac{1}{T_{Rec}} \sum_{t:CFNAI_{t-1} \leq -0.7} \widehat{\lambda}_t$.

At the quarterly frequency, we see the familiar procyclical DS risk premium that is much larger in absolute value in recessions at -25.59% ($t = -2.31$) versus -3.64 ($t = -1.89$) in expansions. The difference is large and significant at -21.95% ($t = -1.95$). In contrast, the TS risk premium is consistently positive at 6.04% ($t = 3.41$) in expansions and 3.84% ($t = 0.54$) in recessions. Interestingly, the time-variation in the DS risk premium is similar to the market risk premium, which is countercyclical at 24.62% ($t = 2.36$) in recessions versus -2.15% ($t = -1.06$) in expansions.

The inclusion of characteristics eradicates the time-variation in the DS risk premium to a large extent, leaving an economically large, but considerably smaller and insignificant risk premium in recessions of -8.93% ($t = -1.33$). The TS risk premium remains positive, large and significant in expansions at 4.37% ($t = 3.13$), but turns insignificantly negative in recessions. The countercyclical MKT risk premium is robust to the inclusion of characteristics. Further, the Size effect is negative in both states of the world, although much stronger in recessions. In contrast, BM and MOM are positive in expansions alone.

To conclude, at both frequencies, I find that only the DS risk premium varies meaningfully over the business cycle. Both in expansions and recessions, the DS risk premium is eradicated largely when controlling for SMB in time-series regressions and Size in cross-sectional regressions. This finding is unsurprising given that the risk premium for SMB (in the time-series) and Size (in the cross-section) is considerably larger in recessions than in expansions, at 10% versus 1% and -4% versus -1.5%, respectively.

Also conditionally, this risk premium is inconsistent with how DS predicts aggregate stock market returns. For instance, Henkel et al. (2011) find that DS predicts positively and particularly so in recessions. However, this time-variation is consistent with the Size effect and natural given that a countercyclical market risk premium implies that risk aversion is larger in recessions and this is the exact time when the investor is most worried about defaults. The absence of similar variation in the TS risk premium is perhaps consistent with the idea that the slope of the yield curve is commonly used as a leading indicator of recessions (Adrian and Estrella (2008)). As a result, TS is most strongly related to the investment opportunity set in expansions, which counterbalances the countercyclical variation in risk aversion.

IV State variables versus Fama and French (1993)

This section analyzes how the ICAPM state variables relate to both the Fama and French (1993) factors (SMB and HML) and their underlying characteristics (Size and Book-to-Market) in a uniform framework. 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. (2011), among others.

To start, I additionally include SMB and HML in each rolling window, such that exposures are estimated in a six-factor model similar to equations (2) and (3). In this section, I analyze the state variable risk premiums. To conserve space, I present results only for the quarterly frequency, but the results are similar at the monthly frequency. In unreported results, I find that the post-ranking exposures of the ICAPM factor mimicking portfolios are only slightly smaller and less significant than what they are in the case without SMB and HML. Thus, we can identify stocks ex ante that hedge the part of the ICAPM risk factors that cannot be hedged by investing in SMB and HML alone.

A Mimicking portfolios

Table VI is similar to Tables III and V and presents average returns, Sharpe ratios and FF3M alphas over the full sample as well as average returns in CFNAI expansions and recessions (all annualized).

Insert Table VI about here.

First, consistent with most previous literature, both SMB and HML capture a positive risk premium of about 2% to 4%, which is significant only for the latter. Perhaps unsurprisingly, both premiums are eradicated completely in the FF3M. Moreover, both premiums are countercyclical, which is especially true for SMB at a significant 14% to 26% in recessions versus zero in expansions. Second, again, a DY risk premium is absent unconditionally as well as in both states of the business cycle. Third, in all weighting schemes but HML_{MVW}, we find a significant negative DS risk premium that ranges from -5.81% to –1.85% ($p < 0.10$) and that is captured largely in the FF3M. Furthermore, in all weighting schemes, the DS risk premium is lower in recessions, but now this time-variation is only large and significant in case of w_{FMB}. Finally, the TS risk premium is positive in all weighting schemes ranging from an insignificant 1.49% for HML_{MVW} to a large and significant 3% to 4% ($p < 0.05$) for the remaining weighting schemes. Again, this premium is not captured well in the FF3M and is most robust in expansions.

I conclude that the state variable risk premiums are quite robust in size and sign to controlling for exposures to SMB and HML. The various mimicking portfolios for DS, TS and HML typically obtain an unconditional risk premium that is large and significant. These risk premiums translate to annualized Sharpe ratios of about 0.25 to 0.40, which is slightly smaller than what we had before in the case of DS and TS.

B Cross-sectional regressions

Table VII presents cross-sectional regressions for the six-factor model similar to Table IV.

Insert Table VII about here.

Over the full sample and without characteristics, the TS and DS risk premiums are only slightly smaller than in the case without SMB and HML at a large and significant -5.81% ($t = 2.63$) and 4.13% ($t = 2.53$), respectively. The risk premium for exposure to MKT, SMB and HML is positive at about 2%, but only the latter is marginally significant. The inclusion of characteristics changes the risk premiums for DS, SMB and HML considerably. For DS, the risk premium is forced down to a marginally significant -2.35% ($t = -1.66$), whereas the risk premiums for SMB and HML are eradicated completely. Again, however, it is comforting to see that the TS risk premium remains large and significant at 2.91% ($t = 2.21$).

Over the business cycle, we see the usual variation for DS without characteristics, from -3.10% ($t = -1.94$) in expansions to -21.34% ($t = -1.89$) in recessions. The TS risk premium is positive in both states, but large and significant in expansions alone at 4.67% ($t = 2.94$). Both the MKT and SMB risk premiums are strongly countercyclical, whereas the HML risk premium is positive and similarly large in both states. When characteristics are included, we see that only the countercyclical MKT risk premium and the TS risk premium in expansions survive.

To conclude, the TS risk premium is robust to the inclusion of both SMB and HML and their underlying characteristics in cross-sectional regressions.[27] In these regressions, the procyclical DS risk premium is not captured by the inclusion of SMB and HML, but it is eradicated almost completely upon the inclusion of characteristics. The "failure" of SMB and HML is perhaps surprising considering that the DS risk premium is (i) captured well

[27] 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 and significant at over 3% in seven (except among Big and low Book-to-Market stocks). These results are available upon request.

in the FF3M in time-series regressions (Tables III and V) and (ii) less time-varying when controlling for exposures to SMB and HML (Table VI). In contrast, given the evidence so far, the "success" of characteristics, and Size in particular, is natural. Similar to DS, both SMB and HML are captured well by characteristics.

In sum, the evidence in this section suggests that exposures to SMB and DS are priced largely because these correlate with the underlying characteristic Size. Although HML and TS are correlated risk factors, I find that a similar conclusion only applies for HML, which is eradicated by the inclusion of Book-to-Market. The survival of the TS risk premium is a strong and novel result, because previous work in Petkova (2006) and Hahn and Lee (2006) suggests that HML and TS are subtitutes in pricing a set of 25 Size and Book-to-Market portfolios. I cannot replicate this result in the cross-section of individual stocks. On top of that, the present evidence suggests that TS is even separate (to a considerable extent) from Book-to-Market, which is favored in this type of test, because it does not suffer from any measurement error.

V Robustness checks

A Innovations in the risk-free rate

A number of previous studies include the three-month t-bill rate (RF) in the set of state variables. I exclude RF, because it is largely redundant in the presence of TS. To validate this claim, Table VIII presents cross-sectional regressions for portfolios (i.e., 25 size and book-to-market and 5 industry portfolios as in Kan et al. (2012)) as a benchmark in Panel A, and for individual stocks in Panel B. Model (1) includes all innovations from the extended five-variable VAR, wherein the correlation between TS and RF is large at -0.78; Model (2) excludes RF; Model (3) excludes TS; Model (4) uses RF and TS orthogonalized from RF; and Model (5) uses RF orthogonalized from TS and TS. As is common in the literature, I use full sample betas for portfolios.[28] For individual stocks, I use the ex ante betas

[28] The results are similar for periodically updated betas.

used throughout. To be consistent with previous work, I present results for the monthly frequency. The quarterly results are similar, however.

Insert Table VIII about here.

A.1 30 Portfolios

First, we see that Model (1) explains the cross-section of portfolios well at an R^2 of 0.74. The risk premiums for TS and RF are large at 59.86% and -25.82%, respectively, but only the former is significant. Interestingly, Models (2) and (3) show that the R^2 drops only marginally when RF is excluded (to 0.67), whereas it drops sharply when TS is excluded (to 0.45). Further, in Model (4) we see that TS|RF adds to a model that already includes RF, at a marginally significant risk premium of 39.73% ($t = 1.87$). Model (5) shows that the reverse is not true, as RF is insignificant and reverses sign.[29]

In sum, these results suggest that it is largely the part of RF that is spanned by TS that is priced, whereas there is a part of TS that is not spanned by RF, but priced. This multicollinearity problem is also clear from the exposures. The cross-sectional correlation between $\delta_{i,TS}$ and $\delta_{i,RF}$ from Models (2) and (3) equals -0.86, but is wildly different in Model (1) at 0.65.

A.2 Individual stocks

We cannot conclude that TS has much to add to a model that already includes RF in the cross-section of individual stocks. Having said that, relative to Models (1) to (3), TS|RF remains positive and nonnegligble economically at 1.82% ($t = 1.42$) in Model (4), whereas the risk premium for RF|TS switches sign in Model (5).[30] Moreover, for individual stocks, $\delta_{i,TS,t-1}$ and $\delta_{i,RF,t-1}$ are also sensitive to the methodology, given an average cross-sectional correlation from Models (2) and (3) of about -0.70, but within Model (1) of 0.69. Thus, it

[29] Similarly, Lioui and Poncet (2011) show that the results for the VAR-ICAPM (and, in particular, RF) are sensitive to the orthogonalization procedure.

[30] Note, these risk premiums are smaller, because the range in exposures within 30 portfolios is far below one, such that the cross-sectional risk premium is scaled up.

is again clear that the return space spanned by the two factors overlaps for a large part, whereas TS is the most important of the two factors.[31] On top of this, the exclusion of RF is attractive, because this allows me to estimate one beta less per stock, per period.

B Cross-sectional regressions using mimicking portfolios as factors

The maximum correlation portfolio of Breeden et al. (1989), which projects the non-traded factor on the test assets, gives identical total risk premiums (amount of risk times risk premium) as the non-traded factor, whether or not the asset pricing model is true (Hou and Kimmel (2009)). Since I am unable to estimate this portfolio and use an out-of-sample procedure, this exact identity is lost. Therefore, Table IX tests whether this identity holds approximately by running cross-sectional regressions that use exposures with respect to the traded mimicking portfolios. The procedure to estimate these exposures is similar to equations (2) and (3), with

$$\left(\widehat{\alpha_{i,t-1}}, \widehat{\beta_{i,m,t-1}}, \widehat{\delta^{mp}_{i,t-1}}\right) = \underset{\alpha_{i,t-1},\beta_{i,m,t-1},\delta^{mp}_{i,t-1}}{\arg\min} \sum_{\tau=1}^{t-1} K(\tau)\left(r_{i,\tau} - \alpha_{i,t-1} - \beta_{i,m,t-1} r_{m,\tau} - \delta^{mp\prime}_{i,t-1} r^{mp}_{\tau}\right)^2, \tag{10}$$

where $r^{mp}_{\tau} = (r^{mp}_{DY,\tau}, r^{mp}_{DS,\tau}, r^{mp}_{TS,\tau})'$, the vector of mimicking portfolio returns, and the superscript mp indicates either HML_{MVW}, HML_{EW}, w_{beta} or w_{FMB}.

I present Fama-MacBeth cross-sectional regressions without characteristics at the quarterly frequency, but the results are similar at the monthly frequency.[32] The sample period is 1972Q2 to 2010Q4, because the use of out-of-sample betas shrinks the sample by five years. As a benchmark, I present results for the non-traded innovations as factors in the first two rows. In the remaining rows, the type of mimicking portfolio used is given in the

[31] Consistent with this conclusion, I find that including the largest principal component of the two factors gives results most similar to those when including TS alone.

[32] The inclusion of characteristics does not add any insight and has the same exact effect for the DS and TS risk premiums as in the previous sections.

first column. I scale the estimated risk premiums for DY, DS and TS to facilitate their interpretation as total risk premiums.[33]

Insert Table IX about here.

First and foremost, we see that the risk premiums for exposure to the mimicking portfolios of DS and TS are consisten in sign and economically large, but slightly smaller in absolute value. In case of DS, the risk premiums range from -3.84% ($t = -1.52$, for w_{beta}) to -5.04% ($t = -2.16$, for HML_{MVW}), relative to -6.42% ($t = 2.59$) for the non-traded factor. In case of TS, the risk premiums range from 3.06% ($t = 1.36$, for w_{beta}) to 4.73% ($t = 1.95$, for w_{FMB}), relative to 4.97% ($t = 2.57$) for the non-traded factor. A likely explanation for the discrepancy is that the re-estimation of exposures in each rolling window has added a second round of noise.

Over this shorter sample period, the risk premium for exposure to non-traded DY innovations increases to an insignificant 2%. Strikingly, the risk premiums for DY mimicking portfolios are even larger and typically significant, ranging from 1% to 5%. I interpret such a large DY risk premium cautiously, as this result is likely to be an artefact of the methodology, as well. For instance, these mimicking portfolios are not orthogonalized from the market and are much more correlated among each other than the non-traded factors. Further, in unreported results, I find that the large premiums for DY mimicking portfolios are easily eradicated when including characteristics.

In all, the evidence is unambiguous and in favor of a negative DS and a positive TS risk premium that is economically large. Combined with the fact that the cross-sectional R^2's are only slightly larger for the mimicking portfolios than for the non-traded innovations, these results suggest that the two are similarly informative about the cross-section of expected returns.

[33] To be specific, for each cross-sectional regression, I multiply the estimated risk premiums for DY, DS and TS with the pre-ranking exposure of a market value-weighted High minus Low quintile portfolio, which is constructed from a one-dimensional sort on exposures to each factor as in Table II. This means that if two risk premiums are equal, roughly the same spread in expected returns is explained.

VI Conclusions

This paper is the first to show that exposure to three state variables known to describe investment opportunities in various asset classes (Dividend Yield (DY), Default Spread (DS) and Term Spread (TS)) can be hedged well in the cross-section of individual stocks. This finding is an important addition to the ICAPM literature, which has focused almost exclusively on answering whether these state variables are priced in a small set of predetermined portfolios. As a result, little guidance could be offered to practitioners who desire to hedge. Moreover, the risk premiums I estimate in the cross-section of individual stocks expose a new and interesting dimension along which state variable risk is priced, as existing portfolio-level estimates are mixed and inconclusive.

To be precise, I find that exposure to innovations in DS and TS is priced at about -4.5% and +5.5%, respectively, whereas exposure to DY risk is not. Moreover, the DS risk premium is solely realized in recessions. I argue that these premiums are consistent with Merton's (1973) ICAPM, that is, each variable's impact on future investment opportunies. Also, I show that the DS risk premium is a Size effect, whereas the TS risk premium is largely separate from the Fama and French (1993) factors and characteristics. Thus, in contrast to previous literature, I cannot conclude that SMB and HML proxy for intertemporal risk. However, my results do add to the debate on whether rationally priced risks or irrationally mispriced characteristics determine expected returns.

A number of extensions come to mind. First, I have largely ignored how 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 relates to questions in the literature on optimal portfolio choice (see, e.g., Kan and Zhou (2007)). Third, it is unlikely that the state variables used in this paper capture all there is to know about investment opportunities. I focus on the most commonly used set that is well-established in the literature. Nevertheless, it could be fruitful to consider alternatives, such as the VIX-index. Another interesting alternative, the Cochrane and Piazzesi (2005) factor, is found to be priced similar to TS in unreported results. Fourth, in future work the time-series may be linked directly to the cross-section by imposing intertemporal restrictions on the risk prices. However, doing this requires a better proxy of the wealth portfolio, and perhaps a set of test portfolios that span the cross-section.

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Table I: Post-ranking exposures of individual stock-based mimicking portfolios

This table presents post-ranking exposures for various zero-investment, mimicking portfolios for innovations in the Dividend Yield (ε_{DY_t}), Default Spread (ε_{DS_t}) and Term Spread (ε_{TS_t}), in Panels A to C. The post-ranking exposures are estimated from $r^{mp}_{k,t} = \alpha + \beta_m r_{m,t} + \delta'[\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t}]' + u_t$, where the innovations in the state variables come from a full-sample VAR. I present results for the single-sorted Market Value Weighted (MVW) portfolios as well as for the four mimicking portfolios described in Section I.B: HML_{MVW}, HML_{EW}, w_{beta} and w_{FMB} (the portfolio implicit in the Fama-MacBeth cross-sectional regression procedure). In addition, I include two benchmarks. First, the Fama and French (1993) factors SMB and HML in Panel D. Second, I sort 25 Size and Book-to-Market portfolios out-of-sample using the same procedure that was used for individual stocks. For this sort, I present results for a portfolio that is long (short) the five highest (lowest) exposure portfolios, HML^p_{EW}, in Panel E. For each mimicking portfolio, I present estimated betas (omitting the intercept) and R^2's at the quarterly (left block) and monthly (right block) frequency. ***,**,* indicate significance at the 1%, 5% and 10%-level , respectively, using White's heteroskedasticity-consistent standard errors. The sample of post-ranking returns spans from April or Q2 1967 to December or Q4 2010.

		Quarterly data					Monthly data				
		β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2	β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2
Panel A: Dividend Yield (DY)											
Single	H	1.32***	0.23***	0.06	-0.13***	0.87	1.29***	0.18***	-0.02	0.06*	0.81
(MVW)	2	1.10***	0.05	0.02	0.00	0.90	1.14***	0.11***	-0.04*	0.04	0.86
	3	0.93***	0.00	0.06***	0.02	0.94	0.96***	0.00	0.02	0.01	0.90
	4	0.84***	-0.04**	-0.01	0.00	0.93	0.86***	-0.08***	0.01	-0.01	0.88
	L	0.98***	-0.02	0.03	-0.01	0.88	0.91***	-0.08***	0.02	-0.04*	0.84
HML_{MVW}		0.34***	0.25***	0.02	-0.12**	0.27	0.38***	0.26***	-0.05	0.09*	0.22
HML_{EW}		0.10*	0.12*	0.06	-0.03	0.06	0.11***	0.16***	-0.04	0.07	0.07
w_{beta}		0.10**	0.11*	0.04	-0.03	0.06	0.11***	0.16***	-0.04	0.07	0.08
w_{FMB}		0.17**	0.29***	-0.06	0.00	0.18	0.26***	0.44***	-0.06	0.07	0.19
Panel B: Default Spread (DS)											
Single	H	1.04***	0.11**	0.06**	-0.06**	0.87	0.97***	0.09***	0.01	0.02	0.87
(MVW)	2	0.89***	-0.01	0.03*	0.03	0.94	0.89***	-0.06***	-0.01	-0.04**	0.92
	3	0.94***	-0.04	0.03	0.01	0.88	0.98***	-0.06***	0.03*	-0.03***	0.93
	4	1.11***	0.00	0.03	0.02	0.87	1.08***	0.02	0.02	0.01	0.87
	L	1.30***	0.10*	-0.03	0.06	0.82	1.30***	0.11***	-0.02	0.04*	0.83
HML_{MVW}		-0.26***	0.01	0.09**	-0.12	0.10	-0.33***	-0.02	0.04	-0.02	0.16
HML_{EW}		-0.16**	0.03	0.08*	-0.03	0.04	-0.18***	0.00	0.02	-0.02	0.08
w_{beta}		-0.16**	0.03	0.10**	-0.04	0.06	-0.18***	-0.01	0.00	-0.02	0.09
w_{FMB}		-0.21**	-0.03	0.31**	-0.04	0.17	-0.23***	0.01	0.06	-0.01	0.05

Table I continued

		Quarterly data					Monthly data				
		β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2	β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2
Panel C: Term Spread (TS)											
Single	H	1.12***	0.10*	-0.06*	0.10***	0.79	1.11***	0.23***	0.04	0.07***	0.80
(MVW)	2	1.00***	0.03	0.01	0.04	0.88	1.07***	0.13***	0.01	0.06***	0.85
	3	0.92***	-0.04	0.01	0.04*	0.92	0.99***	0.05***	0.01	0.00	0.91
	4	0.93***	-0.01	0.07***	-0.03	0.92	0.93***	-0.05***	0.01	-0.02*	0.93
	L	1.06***	0.07	0.04	-0.05*	0.88	1.01***	-0.09***	0.00	-0.05**	0.87
HML_{MVW}		0.06	0.02	-0.11*	0.15***	0.03	0.10**	0.32***	0.04	0.12***	0.15
HML_{EW}		-0.07	-0.05	-0.06	0.11**	0.04	0.04	0.17***	0.05*	0.07**	0.09
w_{beta}		-0.05	-0.06	-0.06	0.09**	0.04	0.04*	0.15***	0.04	0.05**	0.09
w_{FMB}		-0.03	-0.03	0.02	0.18**	0.06	-0.09	0.08	0.11**	0.11**	0.05
Panel D: Benchmark I - Fama and French (1993) factors											
SMB		0.29***	0.07*	0.00	0.05	0.21	0.21***	0.06*	-0.01	0.05*	0.10
HML		-0.24***	-0.02	-0.17***	0.16***	0.21	-0.21***	-0.04	-0.02	0.09***	0.12
Panel E: Benchmark II - 25 Size and Book-to-Market portfolios sorted OOS											
HML^p_{EW}	DY	0.15**	0.10	-0.04	0.02	0.05	0.19***	0.12***	-0.04	0.09**	0.09
HML^p_{EW}	DS	-0.09	-0.04	0.05	-0.08	0.01	-0.14***	-0.03	0.00	-0.04	0.03
HML^p_{EW}	TS	-0.08	-0.02	-0.06	0.11***	0.03	-0.03	0.18***	-0.01	0.10***	0.06

Table II: Pre-ranking characteristics of mimicking portfolios

This table is similar to Table I and presents average Pre-ranking exposure ($\delta_{k,pre}$ for k=DY,DS,TS), Turnover (annualized), Size ($ billion), Book-to-Market and Momentum for the mimicking portfolios of interest at the quarterly and monthly frequency. Book-to-Market is calculated 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) dividend by Market Capitalization (Size) at year-end. Momentum is $\prod_{j=4}^{1}(1+r_{i,t-j})$ and $\prod_{j=12}^{2}(1+r_{i,t-j})$ at the quarterly and monthly frequency, respectively. For HML_{MVW}, HML_{EW} and w_{beta}, $Turnover = \frac{\sum_i \left| w_{i,t-1}\left(\frac{1}{2}\sum_i |w_{i,t-2}(1+r_{i,t-1})|\right) - w_{i,t-2}(1+r_{i,t-1})\right|}{\sum_i |w_{i,t-2}(1+r_{i,t-1})|}$. For w_{FMB}, $Turnover = \frac{\sum_i |w_{i,t-1} - w_{i,t-2}(1+r_{i,t-1})|}{\sum_i |w_{i,t-2}(1+r_{i,t-1})|}$. For Size, BM and MOM the table includes a standard t-test of the null hypothesis that the average characteristic equals zero. ***, ** and * indicate significance at the 1%, 5% and 10%, respectively. Pre-beta and Turnover are positive by construction.

	Quarterly data					Monthly data				
	$\delta_{k,pre}$	Turnover	Size	BM	MOM	Pre-beta	Turnover	Size	BM	MOM
Panel A: Dividend Yield (DY)										
HML_{MVW}	0.88	1.67	-20.26***	0.12***	0.07**	0.57	2.75	-11.15***	0.05***	0.08***
HML_{EW}	0.98	1.84	-1.10***	0.13***	0.01	0.64	2.97	-1.15***	0.11***	0.02
w_{beta}	0.94	1.47	-1.00***	0.12***	0.01	0.60	2.23	-1.07***	0.10***	0.02
w_{FMB}	1.00	1.48	-1.49***	0.15***	0.04	1.00	2.26	-1.42***	0.14***	0.06**
Panel B: Default Spread (DS)										
HML_{MVW}	0.95	1.62	5.22*	-0.21***	-0.09**	0.59	2.38	11.61***	-0.04***	-0.04**
HML_{EW}	1.03	1.72	0.81***	-0.36***	0.00	0.61	2.80	0.90***	-0.21***	0.02**
w_{beta}	0.98	1.36	0.75***	-0.33***	0.00	0.58	2.16	0.93***	-0.20***	0.02**
w_{FMB}	1.00	1.50	0.99***	-0.44***	0.03	1.00	2.29	1.19***	-0.39***	0.03*
Panel C: Term Spread (TS)										
HML_{MVW}	0.90	1.57	-7.41***	0.21***	0.00	0.63	2.33	-28.54***	0.25***	0.10***
HML_{EW}	1.02	1.75	-1.23***	0.16***	-0.01	0.69	2.75	-1.84***	0.17***	0.02
w_{beta}	0.97	1.38	-1.21***	0.16***	-0.01	0.64	2.09	-1.58***	0.15***	0.02*
w_{FMB}	1.00	1.46	-0.77***	0.15***	0.02	1.00	2.22	-1.55***	0.29***	0.02

Table III: Unconditional risk premiums of mimicking portfolios

This table presents the unconditional performance of the mimicking portfolios in a similar fashion as Table I. To be specific, I present average return (μ), standard deviation (σ) and Sharpe ratio (θ) as well as CAPM, Fama-French three-factor model and Carhart's four-factor model alphas (α) (all annualized). ***,**,* indicate significance at the 1%, 5% and 10%-level, respectively, using White's heteroskedasticity-consistent standard errors.

		Quarterly data						Monthly data					
		μ	σ	θ	α_{CAPM}	α_{FF3M}	α_{FFCM}	μ	σ	θ	α_{CAPM}	α_{FF3M}	α_{FFCM}
Panel A: Dividend Yield (DY)													
Single	H	6.80*	26.08	0.26	-0.50	0.99	-0.10	6.77*	23.42	0.29	0.09	1.08	2.97*
(MVW)	2	6.97**	20.92	0.33	0.90	1.97**	2.14**	6.15**	19.89	0.31	0.26	1.25	2.46**
	3	5.65**	17.28	0.33	0.51	0.76	0.01	4.45*	16.36	0.27	-0.51	-0.57	-0.04
	4	5.84**	15.62	0.37	1.22*	1.10	0.97	6.47***	14.73	0.44	2.05**	1.72**	1.20
	L	6.81**	18.75	0.36	1.40	1.56*	1.77*	5.17**	16.06	0.32	0.48	0.36	-0.63
HML_{MVW}		-0.01	15.45	0.00	-1.90	-0.56	-1.86	1.60	16.00	0.10	-0.39	0.72	3.60
HML_{EW}		0.22	10.82	0.02	-0.34	0.08	-0.97	0.35	12.32	0.03	-0.23	0.85	2.94
w_{beta}		0.28	10.01	0.03	-0.29	0.14	-0.83	0.20	11.40	0.02	-0.35	0.61	2.62
w_{FMB}		0.46	14.60	0.03	-0.49	0.27	2.01	2.00	19.29	0.10	0.63	1.39	4.60
Panel B: Default Spread (DS)													
Single	H	5.78*	20.17	0.29	0.05	2.37**	1.86*	6.83***	16.86	0.41	1.83*	2.63***	2.13**
(MVW)	2	5.04**	16.49	0.31	0.14	-0.04	0.20	5.93***	15.06	0.39	1.32*	1.66**	1.03
	3	6.99**	17.97	0.39	1.82**	0.82	0.83	5.30**	16.49	0.32	0.23	0.42	0.56
	4	8.61***	21.33	0.40	2.52**	1.93*	1.95*	4.75*	18.67	0.25	-0.81	-0.53	0.86
	L	7.85**	25.82	0.30	0.70	-0.03	0.49	4.71	23.03	0.20	-1.99	-1.91	-0.83
HML_{MVW}		-2.07	15.15	0.14	-0.65	2.40	1.36	2.13	12.95	0.16	3.82**	4.53***	2.96*
HML_{EW}		-4.85**	13.03	0.37	-3.97**	-0.98	-0.30	-3.14**	9.47	0.33	-2.23*	-1.28	-2.80**
w_{beta}		-4.98***	12.19	0.41	-4.09**	-1.25	-1.14	-2.88**	9.04	0.32	-1.97	-1.22	-2.73**
w_{FMB}		-6.90***	15.80	0.44	-5.77***	-3.04	-5.56	-5.54**	15.90	0.35	-4.38*	-2.27	-4.41*

Table III continued

		Quarterly data						Monthly data					
		μ	σ	θ	α_{CAPM}	α_{FF3M}	α_{FFCM}	μ	σ	θ	α_{CAPM}	α_{FF3M}	α_{FFCM}
Panel C: Term Spread (TS)													
Single	H	8.19**	22.74	0.36	2.03	2.19	2.59	7.23**	20.61	0.35	1.47	0.72	2.39
(MVW)	2	7.62***	19.19	0.40	2.12*	1.58*	1.75*	6.70**	18.91	0.35	1.16	1.52	2.15*
	3	5.69**	17.29	0.33	0.61	0.01	0.25	4.89*	16.73	0.29	-0.23	-0.11	0.50
	4	5.10*	17.34	0.29	0.00	0.80	0.71	4.94**	15.49	0.32	0.16	0.28	0.32
	L	2.90	20.34	0.14	-2.94**	-1.05	-1.03	4.39*	17.55	0.25	-0.83	0.46	-0.11
HML_{MVW}		5.29**	14.42	0.37	4.96**	3.24	3.62	2.84	14.48	0.20	2.30	0.26	2.51
HML_{EW}		5.72***	10.23	0.56	6.09***	4.18***	3.42**	4.24***	9.48	0.45	4.04***	3.13**	4.54***
w_{beta}		5.79***	9.50	0.61	6.06***	4.34***	3.82***	3.90***	8.61	0.45	3.66***	2.91**	4.09***
w_{FMB}		5.71***	12.13	0.47	5.91***	4.15**	4.77***	5.73***	13.78	0.42	6.20***	3.29*	3.97**

Table IV: Fama-MacBeth cross-sectional regressions for individual stocks
This table presents cross-sectional regressions (from April or Q2 1967 to December or Q4 2010) for individual stocks at the quarterly (Panel A) and monthly (Panel B) frequency for the four-factor ICAPM-model excluding (Model (1)) and including (Model (2)) characteristics. I present annualized average risk premiums and cross-sectional R^2's over the full sample in rows 1 to 4. The remaining rows in these panels present estimates in expansions, in recessions and the corresponding difference. Underneath each estimate are Fama-MacBeth t-statistics in brackets, which use the time-series standard deviations of the quarterly or monthly slopes. Recessions periods follow a $CFNAI$-value ≤ -0.7. As a benchmark, I present full sample results for the Fama-French three-factor model (FF3M) at the quarterly frequency in Panel C.

	λ_0	λ_{MKT}	λ_{DY}	λ_{DS}	λ_{TS}	λ_{Size}	λ_{BM}	λ_{MOM}	R^2
				Panel A: Quarterly data					
(1) Full	7.35	1.83	0.46	-6.90	5.71				3.72
	(3.75)	(0.75)	(0.21)	(-2.89)	(3.12)				
(2) Full	27.54	1.99	-0.43	-2.51	3.61	-1.68	3.71	3.49	6.75
	(3.75)	(1.01)	(-0.24)	(-1.69)	(2.63)	(-3.03)	(4.55)	(1.49)	
(1) Exp.	9.04	-2.15	-0.07	-3.64	6.04				3.32
	(4.73)	(-1.06)	(-0.03)	(-1.89)	(3.41)				
(1) Rec.	-2.29	24.62	3.52	-25.59	3.84				5.99
	(-0.32)	(2.36)	(0.45)	(-2.31)	(0.54)				
(1) Diff.	-11.32	26.77	3.60	-21.95	-2.20				2.67
	(-1.54)	(2.52)	(0.44)	(-1.95)	(-0.30)				
(2) Exp.	23.53	-0.77	-0.53	-1.39	4.37	-1.23	3.99	6.60	6.26
	(2.99)	(-0.43)	(-0.29)	(-1.09)	(3.13)	(-2.05)	(4.69)	(3.23)	
(2) Rec.	50.57	17.81	0.16	-8.93	-0.73	-4.21	2.09	-14.32	9.55
	(2.52)	(2.29)	(0.03)	(-1.33)	(-0.16)	(-3.11)	(0.82)	(-1.43)	
(2) Diff.	27.05	18.58	0.69	-7.54	-5.10	-2.98	-1.90	-20.91	3.29
	(1.25)	(2.33)	(0.12)	(-1.10)	(-1.06)	(-2.01)	(-0.71)	(-2.05)	
				Panel B: Monthly data					
(1) Full	8.04	1.23	2.00	-5.54	5.73				2.68
	(4.94)	(0.49)	(0.69)	(-2.31)	(2.75)				
(2) Full	33.70	2.61	2.28	-0.54	2.89	-2.26	3.05	6.47	5.02
	(5.21)	(1.18)	(0.97)	(-0.31)	(1.75)	(-4.37)	(4.57)	(3.46)	
(1) Exp.	8.66	-1.26	0.96	-2.42	5.65				2.59
	(5.23)	(-0.49)	(0.31)	(-1.03)	(2.80)				
(1) Rec.	4.39	15.77	8.04	-23.71	6.23				3.20
	(0.80)	(1.90)	(0.96)	(-2.71)	(0.78)				
(1) Diff.	-4.28	17.03	7.08	-21.28	0.58				0.61
	(-0.75)	(1.97)	(0.79)	(-2.35)	(0.07)				
(2) Exp.	30.04	0.60	2.18	0.71	3.14	-1.88	3.34	9.27	4.90
	(4.33)	(0.26)	(0.86)	(0.40)	(1.93)	(-3.36)	(4.85)	(5.31)	
(2) Rec.	54.95	14.27	2.87	-7.81	1.41	-4.46	1.34	-9.80	5.77
	(3.12)	(2.10)	(0.45)	(-1.32)	(0.23)	(-3.38)	(0.63)	(-1.31)	
(2) Diff.	24.91	13.66	0.69	-8.52	-1.73	-2.57	-2.00	-19.06	0.87
	(1.32)	(1.91)	(0.10)	(-1.37)	(-0.27)	(-1.79)	(-0.89)	(-2.48)	
				Panel C: Benchmark - FF3M (Quarterly data)					
	λ_0	λ_{MKT}	λ_{SMB}	λ_{HML}		λ_{Size}	λ_{BM}	λ_{MOM}	R^2
(1) Full	6.89	1.78	2.04	2.66					4.25
	(3.71)	(0.74)	(1.30)	(2.03)					
(2) Full	28.63	2.58	0.29	0.15		-1.79	3.59	2.59	6.82
	(4.10)	(1.29)	(0.25)	(0.15)		(-3.40)	(4.73)	(1.10)	

Table V: Risk premiums in CFNAI expansions and recessions

This table is similar to Table I and presents annualized average and risk-adjusted returns for the mimicking portfolios in expansions, recessions and the corresponding difference. As before, recessions periods follow a $CFNAI$-value ≤ -0.7. To conserve space, I present only Fama and French (1993) three-factor model α's. ***,**,* indicate significance at the 1%, 5% and 10% - level, respectively, using White's heteroskedasticity-consistent standard errors.

		Quarterly data						Monthly data					
		Average Return μ			FF3M α			Average Return μ			FF3M α		
		μ_{Exp}	μ_{Rec}	$\mu_{Rec}-\mu_{Exp}$	α_{Exp}	α_{Rec}	$\alpha_{Rec}-\alpha_{Exp}$	μ_{Exp}	μ_{Rec}	$\mu_{Rec}-\mu_{Exp}$	α_{Exp}	α_{Rec}	$\alpha_{Rec}-\alpha_{Exp}$
Panel A: Dividend Yield (DY)													
Single	H	4.96	17.33	12.38	0.45	6.26	5.81	5.74	12.75	7.01	1.37	0.57	-0.80
(MVW)	2	5.46*	15.65	10.19	1.57	6.83**	5.26*	5.20*	11.64	6.44	1.18	1.44	0.26
	3	4.61*	11.59	6.99	0.21	2.16	1.94	3.90	7.67	3.77	-0.80	-0.52	0.28
	4	4.82**	11.66	6.84	0.81	1.67	0.86	5.94**	9.54	3.60	1.04	4.35*	3.31
	L	4.98*	17.27	12.29	0.97	0.38	-0.60	4.84*	7.07	2.22	0.15	0.46	0.31
HML_{MVW}		-0.02	0.06	0.08	-0.52	5.89	6.41	0.89	5.69	4.79	1.22	0.11	-1.11
HML_{EW}		0.30	-0.21	-0.51	0.50	-0.39	-0.89	0.84	-2.51	-3.35	1.42	-4.50	-5.92
w_{beta}		0.16	0.93	0.77	0.39	0.78	0.39	0.51	-1.58	-2.09	1.09	-3.98	-5.07
w_{FMB}		-0.07	3.52	3.60	-0.07	5.20	5.27	0.96	8.04	7.08	1.63	-1.34	-2.97
Panel B: Default Spread (DS)													
Single	H	5.31*	8.49	3.18	2.56**	-1.37	-3.93	7.11***	5.21	-1.90	3.46***	-1.50	-4.95**
(MVW)	2	3.70	12.70	9.00	-0.71	1.50	2.21	5.57**	8.00	2.42	1.23*	2.34	1.10
	3	4.99*	18.45*	13.46	0.04	4.73	4.69	4.12	12.16	8.04	-0.63	4.35**	4.98**
	4	6.37**	21.46	15.09	1.35	1.16	-0.19	3.49	12.11	8.62	-0.97	0.65	1.62
	L	4.79	25.35	20.56	-0.48	1.43	1.91	2.40	18.10	15.69	-2.71**	2.86	5.57
HML_{MVW}		0.51	-16.87**	-17.38**	3.04	-2.80	-5.84	4.71**	-12.88*	-17.59**	6.16***	-4.36	-10.52*
HML_{EW}		-3.20	-14.28**	-11.08*	-0.83	-5.19	-4.36	-1.69	-11.55**	-9.86**	-0.65	-5.10	-4.45
w_{beta}		-3.14*	-15.49**	-12.34**	-0.85	-7.17	-6.32	-1.52	-10.82**	-9.30**	-0.67	-5.11	-4.44
w_{FMB}		-3.64*	-25.59**	-21.95*	-1.70	-20.43	-18.72	-2.42	-23.71***	-21.28**	-0.91	-12.97	-12.06

Table V continued

		Quarterly data						Monthly data					
		Average Return μ			FF3M α			Average Return μ			FF3M α		
		μ_{Exp}	μ_{Rec}	$\mu_{Rec}-\mu_{Exp}$	α_{Exp}	α_{Rec}	$\alpha_{Rec}-\alpha_{Exp}$	μ_{Exp}	μ_{Rec}	$\mu_{Rec}-\mu_{Exp}$	α_{Exp}	α_{Rec}	$\alpha_{Rec}-\alpha_{Exp}$
Panel C: Term Spread (TS)													
Single	H	6.35*	18.76	12.41	3.20*	2.40	-0.80	6.30*	12.61	6.30	1.46	-0.70	-2.15
(MVW)	2	6.64**	13.25	6.61	1.79*	1.31	-0.48	5.91**	11.33	5.43	1.70	0.69	-1.01
	3	4.52*	12.34	7.82	-0.37	0.02	0.38	4.19	8.97	4.78	-0.60	0.95	1.55
	4	3.93	11.78	7.85	0.26	0.74	0.48	4.08*	9.94	5.87	-0.46	2.68	3.14
	L	1.39	11.56	10.17	-1.64	0.41	2.05	4.13	5.90	1.78	0.18	1.29	1.11
HML_{MVW}		4.96**	7.20	2.24	4.83*	1.98	-2.85	2.17	6.70	4.53	1.28	-1.98	-3.26
HML_{EW}		6.29***	2.40	-3.89	5.49***	3.50	-2.00	3.80***	6.74	2.94	3.60**	3.07	-0.53
w_{beta}		6.17***	3.59	-2.59	5.49***	4.63	-0.87	3.61***	5.53	1.92	3.54***	1.82	-1.72
w_{FMB}		6.04***	3.84	-2.20	5.39***	2.30	-3.09	5.65***	6.23	0.58	4.15**	-0.32	-4.47

Table VI: Risk premiums of mimicking portfolios controlling for exposure to SMB and HML

This table is similar to Table III and V and presents annualized risk premiums for mimicking portfolios in the extended six-factor model that includes the market return, the Fama and French factors (SMB and HML, Panels A and B) and the ICAPM factors (DY, DS and TS, Panels C to E) at the quarterly frequency. As before, the pre-ranking betas are estimated jointly using only historical data at the end of each period $t-1$. I present the unconditional average return (μ_{Full}), Fama-French alpha (α_{FF3M}), Sharpe ratio (θ) and average return in CFNAI expansions and recessions (μ_{Exp} and μ_{Rec}). ***,**,* indicate significance at the 1%, 5% and 10%-level, respectively, using White's heteroskedasticity-consistent standard errors.

	Quarterly data				
	μ_{Full}	α_{FF3M}	θ	μ_{Exp}	$\mu_{\mathrm{Re}c}$
Panel A: Size (SMB)					
HML_{MVW}	2.93	-1.52	0.14	-1.09	25.98**
HML_{EW}	3.91	-1.11	0.18	0.15	25.47**
w_{beta}	2.98	-1.19	0.16	-0.24	21.43**
w_{FMB}	2.26	-0.24	0.22	0.20	14.11**
Panel B: Book-to-Market (HML)					
HML_{MVW}	3.19	-1.33	0.20	2.70	5.96
HML_{EW}	4.27**	1.28	0.33	3.69*	7.59
w_{beta}	3.99**	1.17	0.32	3.53*	6.60
w_{FMB}	2.28*	0.85	0.27	2.07*	3.44
Panel C: Dividend Yield (DY)					
HML_{MVW}	-0.50	0.31	0.04	0.45	-5.93
HML_{EW}	-1.18	-0.35	0.14	-0.78	-3.45
w_{beta}	-1.16	-0.45	0.15	-0.73	-3.64
w_{FMB}	0.50	-0.10	0.04	-0.25	4.80
Panel D: Default Spread (DS)					
HML_{MVW}	2.55	4.02**	0.23	2.63	2.11
HML_{EW}	-1.85*	-0.46	0.26	-1.75	-2.43
w_{beta}	-2.06*	-0.64	0.29	-1.45	-5.60
w_{FMB}	-5.81***	-2.53	0.40	-3.10*	-21.34*
Panel E: Term Spread (TS)					
HML_{MVW}	1.49	0.11	0.12	1.93	-1.03
HML_{EW}	3.25**	2.47**	0.34	4.28***	-2.69
w_{beta}	3.33**	2.68**	0.37	4.29***	-2.20
w_{FMB}	4.13**	2.94*	0.38	4.67***	1.04

Table VII: Fama-MacBeth cross-sectional regressions including SMB and HML

This table is similar to Table IV and presents quarterly Fama-MacBeth cross-sectional regressions for the six-factor ICAPM-model that includes SMB and HML (Model (1)) as well as a model that also includes characteristics (Model (2)). I present average risk premiums and cross-sectional R^2's over the full sample in rows 1 to 4. The remaining rows present estimates in expansions, in recessions and the corresponding difference. Underneath each estimate are Fama-MacBeth t-statistics in brackets, which use the time-series standard deviations of the quarterly slopes.

	λ_0	λ_{MKT}	λ_{DY}	λ_{DS}	λ_{TS}	λ_{SMB}	λ_{HML}	λ_{Size}	λ_{BM}	λ_{MOM}	R^2
					Quarterly data						
(1) Full	6.62	2.03	0.50	-5.81	4.13	2.26	2.28				4.81
	(3.51)	(0.92)	(0.27)	(-2.63)	(2.53)	(1.45)	(1.79)				
(2) Full	28.12	2.73	-0.26	-2.35	2.91	0.50	0.04	-1.77	3.52	2.61	7.20
	(4.07)	(1.45)	(-0.16)	(-1.66)	(2.21)	(0.45)	(0.04)	(-3.40)	(4.54)	(1.10)	
(1) Exp.	8.53	-1.74	-0.25	-3.10	4.67	0.20	2.07				4.38
	(4.60)	(-0.98)	(-0.14)	(-1.94)	(2.94)	(0.13)	(1.65)				
(1) Rec.	-4.35	23.67	4.80	-21.34	1.04	14.11	3.44				7.28
	(-0.66)	(2.39)	(0.68)	(-1.89)	(0.17)	(2.48)	(0.73)				
(1) Diff.	-12.88	25.41	5.05	-18.23	-3.63	13.91	1.37				2.89
	(-1.88)	(2.52)	(0.69)	(-1.60)	(-0.57)	(2.37)	(0.28)				
(2) Exp.	25.50	0.39	-0.57	-1.40	3.80	-0.85	0.07	-1.44	3.89	6.03	6.70
	(3.42)	(0.22)	(-0.36)	(-1.15)	(2.84)	(-0.80)	(0.06)	(-2.53)	(4.78)	(3.03)	
(2) Rec.	43.10	16.10	1.57	-7.80	-2.25	8.23	-0.13	-3.66	1.39	-17.00	10.06
	(2.35)	(2.38)	(0.30)	(-1.22)	(-0.52)	(1.93)	(-0.04)	(-2.93)	(0.60)	(-1.62)	
(2) Diff.	17.60	15.70	2.15	-6.40	-6.06	9.08	-0.19	-2.22	-2.50	-23.02	3.35
	(0.89)	(2.25)	(0.39)	(-0.98)	(-1.34)	(2.07)	(-0.05)	(-1.62)	(-1.02)	(-2.16)	

Table VIII: Exclusion of Risk-Free rate from set of ICAPM-factors
This table serves to justify the exclusion of the risk-free rate (RF) from the set of ICAPM factors. I present cross-sectional regressions at the monthly frequency (to be consistent with most previous literature) for (i) a set of 30 portfolios (25 size and book to market and 5 industry, as in Kan et al. (2012)) in Panel A and (ii) individual stocks in Panel B. For portfolios, I estimate the VAR-innovations and first stage betas over the full sample as is usual. For individual stocks, I use the periodically updated VAR and betas used throughout. I consider five models. Model (1) contains all four ICAPM factors and the MKT; Model (2) excludes RF; Model (3) excludes TS; Model 4 includes RF, but TS is orthogonalized from RF (TS|RF); and finally, Model (5) includes RF orthogonalized from TS (RF|TS) and TS itself. I present average estimated risk premiums (with corresponding t-statistics in brackets, based on Shanken (1992) standard errors in Panel A and Fama and MacBeth (1973) standard errors in Panel B) and cross-sectional R^2's (from a regression of average returns on betas in Panel A and the time-series average of the cross-sectional R^2 in Panel B.)

	λ_0	λ_{MKT}	λ_{DY}	λ_{DS}	λ_{RF}	λ_{TS}	R^2
Panel A: Cross-sectional regressions for 30 portfolios							
(1) RF and TS	13.03	-7.21	-5.81	46.07	-25.82	59.86	74.41
	(2.44)	(-1.20)	(-0.57)	(1.87)	(-1.22)	(2.31)	
(2) TS	8.46	-2.66	-4.42	17.80		51.54	66.65
	(1.44)	(-0.41)	(-0.55)	(0.94)		(2.76)	
(3) RF	5.67	0.49	-2.07	-3.83	-45.54		45.04
	(0.97)	(0.07)	(-0.27)	(-0.20)	(-2.59)		
(4) RF and TS|RF	13.03	-7.21	-5.81	46.07	-25.82	39.73	74.41
	(2.44)	(-1.20)	(-0.57)	(1.87)	(-1.22)	(1.87)	
(5) RF|TS and TS	13.03	-7.21	-5.81	46.07	20.87	59.86	74.41
	(2.44)	(-1.20)	(-0.57)	(1.87)	(1.09)	(2.31)	
Panel B: Cross-sectional regressions for individual stocks							
(1) RF and TS	8.09	1.06	0.39	-6.02	-3.38	5.12	2.93
	(4.98)	(0.42)	(0.14)	(-2.59)	(-1.49)	(2.55)	
(2) TS	8.04	1.23	2.00	-5.54		5.73	2.68
	(4.94)	(0.49)	(0.69)	(-2.31)		(2.75)	
(3) RF	8.20	1.32	0.44	-6.27	-3.21		2.73
	(5.01)	(0.52)	(0.15)	(-2.60)	(-1.40)		
(4) RF and TS|RF	8.15	1.06	0.37	-5.95	-3.36	1.82	2.93
	(5.01)	(0.42)	(0.13)	(-2.56)	(-1.49)	(1.42)	
(5) RF|TS and TS	8.10	1.06	0.37	-5.94	0.81	5.34	2.93
	(4.98)	(0.42)	(0.13)	(-2.55)	(0.54)	(2.65)	

Table IX: Cross-sectional regressions with mimicking portfolios of DY, DS and TS as factors

This table is similar to Table IV and presents Fama-MacBeth cross-sectional regressions that use the mimicking portfolios, analyzed in Section II and III, as factors. Due to the out-of-sample nature of the mimicking portfolios, this means that the sample period shrinks by five years and runs from April or Q2 1972 to December or Q4 2010. I present five regressions row-wise, where the set of factors is given in the second column. First, I repeat the risk premium for exposure to the non-traded innovations. Next, I present the risk premiums for exposures to each of four mimicking portfolios, i.e., HML_{MVW}, HML_{EW}, w_{beta} or w_{FMB}. For interpretative purposes, the risk premiums for DY, DS and TS are scaled by the pre-ranking exposure of the HML_{MVW} mimicking portfolio to the factor of interest. For each model, I present the scaled time-series average risk premium $\widehat{\lambda^s_{Full}}$ (with corresponding Fama and MacBeth (1973) t-statistics underneath each estimate) as well as the time-series average cross-sectional $\widehat{R^2}$.

Quarterly data							
Type DY,DS,TS		λ_0	λ_{MKT}	λ_{DY}	λ_{DS}	λ_{TS}	R^2
Non-traded	VAR-innovations	7.73	1.85	2.21	-6.42	4.97	3.29
		(3.72)	(0.73)	(1.05)	(-2.59)	(2.57)	
Mimicking portfolios	HML_{MVW}	8.02	1.70	1.98	-5.04	3.09	3.43
		(3.96)	(0.71)	(0.82)	(-2.16)	(1.45)	
	HML_{EW}	7.72	1.62	4.76	-4.07	3.28	3.90
		(3.78)	(0.69)	(2.29)	(-1.59)	(1.42)	
	w_{beta}	7.66	1.78	4.35	-3.84	3.06	3.90
		(3.76)	(0.75)	(2.06)	(-1.52)	(1.36)	
	w_{FMB}	7.70	1.97	3.59	-4.14	4.73	3.98
		(3.75)	(0.75)	(1.55)	(-1.48)	(1.95)	