Prices of Risk and the Business Cycle[†]

Amir Akbari

McGill University

Francesca Carrieri

McGill University

This version: March 2015

Abstract

We estimate in a linear regression framework an asset pricing model that is both intertemporal and fully conditional. Using time-varying quantities of risks as regressors, we focus our analysis on the time-varying prices of risk to capture investors' assessment of the shift in investment opportunities through the economic cycle. Separately with each information variable, we show that the reward for intertemporal risk is decreasing during recessions with the proxy that negatively predicts market returns. This evidence stands opposite to our findings for the compensation for market risk. When combining all information variables we find that in statistical terms the conditional price for intertemporal risk with this proxy is relatively more significant than the price of market risk at the end of an expansion and during recessions. Thus differences in the two sources of risk are heightened in this phase of the cycle since holding assets with weak or negative correlation with the market becomes crucial especially at these times. The relative importance of intertemporal risk in recessions is also supported by the reduction in the unexplained portion of the asset pricing model for those periods.

[†] We thank Neal Galpin, Spencer Martin, Sergei Sarkissian and seminar participants at the Department of Finance at the University of Melbourne for useful comments. Amir Akbari is a Ph.D. candidate in finance at the Desautels Faculty of Management, McGill University. Email: amir.akbari@mail.mcgill.ca Francesca Carrieri is Associate Professor of Finance at the Desautels Faculty of Management, McGill University, 1001 Sherbrooke Str. West, Montreal, QC, H3A 1G5. Email: francesca.carrieri@mcgill.ca. Carrieri acknowledges financial support from the Social Science and Humanities Research Council and thanks the School of Banking and Finance at the University of New South Wales for hospitality during the completion of the first version of this paper.

1 Introduction

A large body of literature has provided evidence that risk is time-varying and there is also strong support that time-varying risk predicts time-variation in expected returns. By looking at the risk-return relationship through time our paper fits in this strand of literature. We empirically investigate the behavior of the prices of market and intertemporal risk through the business cycle. As we intend to capture investors' assessment of changing investment opportunities in the economy, we use an ICAPM framework that is suited to address the conditional dynamics in the expected compensation for risk.

Estimating and testing the risk-return trade-off of the market portfolio has represented a challenge for the empirical asset pricing literature. The magnitude of the coefficient, its statistical significance and also its sign has been largely debated. A number of possible explanations have been put forward for the conflicting evidence, some theory-based and others justified from the empirical analysis. Part of the literature attributes those findings to some factors that have been omitted in the pricing equation. Indeed from a theoretical standpoint, going back to Merton (1973) seminal paper, expected returns depend on market risk as well as additional risk factors linked to state variables that proxy for changes in the investment opportunity set. The empirical literature that has looked into improving the risk-return relation through the addition of intertemporal risk is now quite extensive. Some papers have restricted the analysis to the time-series for the aggregate stock market, with mixed results. Others have looked at the cross-section and in some cases found inconsistencies.[1]

Our paper estimates a multi-factor model with market risk as well as potential proxies for intertemporal risk, combining long time-series and a large cross-section. Although our approach is in capturing the dynamics of the risk-return trade-off in the time-series, we gain power with the help of the cross-section as we constrain the coefficients in estimating the prices of risk. We adopt the methodology of Bali and Engle (2010) who use time-varying conditional covariances

[1] See among others: Whitelaw (2000), Scruggs and Glabadanidis (2003), Brennan, Wang, and Xia (2004), Gerard and Wu (2006), Hahn and Lee (2006), Ang et al. (2006), Petkova (2006), Guo and Whitelaw (2006), Bali (2008), Guo and Savickas (2008), Chen and Zhao (2009), Ozoguz (2009), Bali and Engle (2010).

of assets with risk factors, generated separately, to estimate the risk-return trade-off within a panel regression. We complement their approach with interaction variables in the regression to estimate the impact of conditioning information. The specification of our empirical asset pricing model is thus internally consistent in the sense that it is both conditional and intertemporal. Our contribution to the literature is then in comparing the dynamics of the market and intertemporal prices of risk through the business cycle when conditioning information is used. This analysis also allows us to assess their relative importance both in economic and in statistical terms.

We start by estimating a specification with time-varying risks where we model the changes in the prices of risk with a dummy variable for the NBER recession periods. We find no statistically significant impact on the expected compensation investors require for either type of risk. We thus implement a fully conditional regression with time-varying prices of risk, in addition to time-varying risks. Our methodology allows us to construct *conditional* confidence intervals around the time-varying prices to understand whether the risk-return tradeoff is significant at a particular level of the commonly used information variables that are proxy for the state of the economy. Our results can then be summarized as follows.

Conditioning on each information variable separately, we find that the price of market risk is statistically different from zero when dividend yield, term premium, default premium and realized volatility are above while short-term interest rates are below their long-term average. Given the sign of the estimated coefficients for each of the variables and the associated conditional standard errors, the price of market risk is increasingly positive with changes in those variables that are associated with movement toward recessions and then decreasing through expansions. The evidence supports that the reward for intertemporal risk is instead decreasing during recessions for the risk factor proxied by the innovations in the short-term risk free rate, the state variable that negatively predict market returns. When we condition on all the variables at the same time, we find that the estimated price of market risk is always lower at the beginning of the recession and increases through the following period. The impact on expected returns from the price of intertemporal risk is more difficult to assess in the case of the different proxies, but the evidence overall suggests that the price is higher at the beginning and decreases over the recession for the proxy that provides hedging value. With the help of the conditional confidence intervals we find the price of market risk is more often significant relative to that of intertemporal risk in expansion periods, while the latter performs relatively better at identifying the expected compensation at the end of an expansion period and over recessions. The relative importance of intertemporal risk in recession periods is also supported by the reduction in the unexplained portion of the asset pricing model.

The time-variation in the relationship between expected returns and risk through the business cycle is thus in line with our intuition from the intertemporal pricing model that the increasing likelihood of recessions lead to revisions in investors' risk preferences. Furthermore, it is also consistent with the empirical evidence from the predictability literature, which suggests that the required reward for risk varies with the information about economic conditions that is publicly available to investors, as for example in Ferson and Harvey (1991). We further provide evidence that conditioning information matters also in identifying significant time-variation in intertemporal risk, and particularly so during downturns, differently from the time-variation that characterizes market risk. Indeed, divergences among multiple sources of risk should be heightened during recession periods, when the riskiness of a portion of the market, such as those assets that are positively correlated with the market, increases. As a result it becomes empirically feasible to capture the hedging component during recessions, since holding assets with weak or negative correlation with the market becomes crucial especially at the end of expansions, when the economy moves toward a downturn. One can thus argue that a higher statistical significance of intertemporal risk documented at the end of expansions and through recessions suggests that, in those times, the latter risk becomes a much larger component of total premia also in economic terms.

The remainder of the paper is organized as follows. Section 2 presents the empirical model and the estimation methodology. The data description is in Section 3. Empirical results are discussed in Section 4. Section 5 concludes.

2 Empirical methodology

2.1 Asset pricing specification

Theoretical intertemporal risk models show that in a dynamic economy, investors are compensated in equilibrium for the contemporaneous exposure of their portfolio to market risk, as well as to the risk of future shifts in the investment opportunity set (see Merton (1973), Campbell (1993)). This is the result of the hedging demands of forward-looking investors who anticipate stochastic changes in investment opportunities and yearn to achieve smooth consumption through time and possible states of nature. Following Merton's (1973), the relationship between asset returns is governed by the following asset pricing equation:

$$E_{t-1}\left[R_t - R_{f,t-1}\right] = \lambda \ Cov_{t-1}\left(R_t, R_{m,t}\right) + \gamma' \ Cov_{t-1}(R_t, z_t)$$

(1)

Where $R_{f,t}$ is the risk free rate, R_t is a vector of N asset returns, $R_{m,t}$ is the market return and z_t are the L state variables that predict changes in the future investment opportunity set, all computed for period t . $E_t[\cdot]$ denotes the conditional expectation operator. Similarly, $Cov_t(R,\cdot)$ denotes the conditional covariance between asset returns and market portfolio (or the state variables) based on the information available at time t. In this model λ denotes the price of market risk (or aggregate relative risk aversion) and γ is a vector of L state variables' sensitivities to capture the price of intertemporal risk. As it is always pointed out in estimating intertemporal risk models, Merton (1973) does not identify directly what the state variables might be, although he mentions the interest rate as a possible candidate. Lacking direct guidance, the empirical literature has explored the relevance of a number of proxies. In our empirical implementation we draw on previous literature and explore a number of potential state variables as explained in the data section.

2.2 Empirical specification for the price of risk

There are different approaches in the empirical asset pricing literature to estimate conditional second moments and the prices of risk of model (1). One strand of the literature implements the Generalized Method of Moments (GMM) procedure (Hansen (1982)) to estimate directly the prices of risk without retrieving the conditional covariances. Another other strand of literature focuses on parameterizing the dynamics of second moments and estimate the prices of risk based on these covariances. Our approach is more similar to the latter, as we fully parameterize all quantities of interest but recover them through a number of steps. We first separately estimate time-varying covariances for each asset, implementing the Asymmetric Dynamic Conditional Correlation (ADCC) specification proposed by Cappiello, Engle, and Sheppard (2006). Then we specify an asset pricing model and estimate the common prices of risk through linear regressions, using the fitted conditional covariances as regressors. Appendix A explains in details the ADCC methodology, similar to the approach of Bali and Engle (2010). For the asset pricing model, Bali and Engle (2010) estimate a constant price of risk. In this paper, we condition the coefficients of the model on the available information variables through interactions. We use the Park estimator to correct for cross correlation, autocorrelations and heteroskedasticity in the error terms and estimate in a panel regression the following equation that is the empirical specification of (1):

$$\begin{aligned} R_{i,t} - R_{f,t-1} &= \alpha_{t-1} + \lambda_{t-1} Cov_{t-1}\left(R_{i,t}, R_{m,t}\right) + \textstyle\sum_{j=1}^{L} \gamma_{t-1,j}\, Cov_{t-1}\left(R_{i,t}, z_{j,t}\right) + \epsilon_{i,t}, \quad \forall\, i, \forall\, t \\ \alpha_{t-1} &= \boldsymbol{\alpha}'\ IV_{t-1} \\ \lambda_{t-1} &= \boldsymbol{\lambda}'\ IV_{t-1} \\ \gamma_{t-1,j} &= \boldsymbol{\gamma}_{\mathbf{j}}'\, IV_{t-1} \end{aligned}$$

(2)

Where $\mathrm{IV_t}$ is a set of K demeaned information variables, including a constant, and the bold symbols are vectors of coefficients. Consistent with ICAPM theory, we construct the panel such that all test assets face equal prices of risk, i.e. λ_t and $\gamma_{t,j}$. When excluding the information variables from the vector $\mathrm{IV_t}$, this specification nests the unconditional model, where the prices of risk are considered to be time invariant. Moreover, choosing information variables as a dichotomous function over time, the specification in equation (2) allows to analyzing the relationship, conditional on specific periods of time. For example, in one of the tests, the $\mathrm{IV_t}$ is a dummy variable that switches to 1 during recessions, to study the changes in the prices of risk in different periods of the business cycle.

In the setting of equation (2) the *conditional* price of market risk, λ_t, is the derivative of the left hand side (excess returns) with respect to the regressor (covariance with the market portfolio). Thus it is straightforward to derive its conditional standard errors from (2), as below:[2]

$$var\left(\frac{\partial R_i}{\partial cov(R_i, R_m)}\middle| IV\right) = var(\lambda_0) + IV^2\, var(\lambda_1) + 2IV\, cov(\lambda_0, \lambda_1) \tag{3}$$

Here, λ_0 is the first element of the vector $\boldsymbol{\lambda}$ and represents the coefficient for the constant in the IV_t while λ_1 is the second element that represents the coefficient for the information

[2] For ease in the exposition we present the case of only one information variable in the IV_t set. Appendix C provides the conditional variances of the estimates in the case of K information variables.

variable in the IV_t. The conditional intercept, α_t, and the conditional price of the intertemporal risk factors, $\gamma_{t,j}$, are similarly estimated. Based on these conditional estimates, confidence intervals are calculated at each time period, for example for a p-value of 5 percent (see appendix C for detailed formulation). In section 4.4.3 we plot the prices of risk with respect to the conditioning information variables. With the help of these plots we can study changes in the price of each risk factor conditional on only one or multiple information variables, both in time domain and information variable domain (i.e. the possible range of the information variable).

As a robustness check, we also implement a simplified version of a multivariate conditional GARCH-in-Mean methodology, in the spirit of De Santis and Gerard (1997), for a model with only one factor. This experiment confirms that the two-step methodology implemented in this paper results in differences with respect to the standard GARCH estimations that are not material for inference. On the other hand, our methodology provides us with the flexibility to estimate with large cross-sections conditional asset pricing models with multiple factors, which are numerically challenging with the standard GARCH approach.

3 Data

This section illustrates the data used in the empirical analysis. We study weekly US stock market returns from January 2nd, 1962 to December 31th, 2013 conditional on a set of information variables. A few macroeconomic variables are used as lagged instruments and as innovations to proxy for an intertemporal risk factor. The weekly frequency is particularly suited to this study, given our goal to capture the impact of the business cycles, and filter out stock characteristics linked to market-microstructures. Over the 2711-week sample, recessions cover 361 weeks, or 13.3 percent. Furthermore, the average duration of a recession is 51.6 weeks, thus a lower frequency would decrease statistical power The choice of the starting and end dates is due to the data availability of the information variables with weekly frequency.

3.1 Test Assets

Inspired by Lewellen, Nagel, and Shanken (2010) and Daniel and Titman (2012), who argue that the usual test assets in cross sectional studies (e.g. 25 size/Book-to-Market portfolios) have strong factor structure, we study our asset pricing model on industry portfolios. Lewellen, Nagel, and Shanken (2010) also recommend testing on individual assets, however, due to the length of the time-period of our analysis, this would result in survival bias and tilt the test assets toward large ones.[3]

We study the 30 US industry portfolios based on their four-digit SIC code, downloaded as daily data from Kenneth French's online data library and compounded linearly to obtain weekly returns. For the market portfolio we use the value-weighted NYSE/ AMEX/ NASDAQ index from CRSP. For the risk free rate, we use the weekly one month T-bill rates, obtained from Kenneth French online data library. Summary statistics of these samples are provided in Table 1.

The dataset under study covers a fairly diverse range of assets and includes several business cycles, which increase the statistical power of our empirical tests. In particular, our dataset in its 2711 weekly observations covers seven recent US economy recessions, as identified by the NBER, as well as some of the major US financial market crashes such as the Black Monday crash in 1987, the Dot-com crash in 2000 and the housing bubble 2008. From the cross section point of view, our sample covers a set of assets that differ uniquely from the other assets (sectors) in their exposure to technological and production shocks.

3.2 State variables

As state variables that can be potentially linked to the shifts in the investment opportunity set, we use bond returns and innovations in macroeconomic variables. Specifically, for our main conditional tests we use returns on US Treasury Bonds with long maturities. CRSP provides daily return on Treasury Bonds with 30, 20, 10, 7, 5, 2 and 1-year maturity. We linearly compound these daily returns to get weekly bond returns and take an equally weighted average of the long maturity ones to get a bond portfolio with maturity over 10 years.[4] The choice of a long-term bond portfolio is supported by both theoretical and empirical papers in the literature. Merton (1977) initially suggests bonds and interest rates as potential state variables. Chen, Roll, and Ross (1986), Scruggs and Glabadanidis (2003), Gerard and Wu (2006) among others, test

[3] For comparison with Bali and Engle (2010) we test our methodology on the 30 individual stocks composing the Dow Jones Industrial Average, from Oct 3rd 1986 to December 2012. Our results are qualitatively unchanged.

[4] In not reported results over a shorter sample, we use returns on the US Government Index All Lives (all maturity bonds) and Over 10 Years (long term maturity bonds) directly computed by DataStream, which are only available from 1980.

this link empirically. We also check the results with an alternative bond measure that takes the average of all maturities.

Innovations to macroeconomic variables are commonly used in the empirical asset pricing literature to proxy for intertemporal risk as drivers of hedging demands, since these variables directly impact the cost of capital, cash-flows and investment opportunities of firms. Accordingly, we test the following set of macroeconomic variables: changes in Term spread (the difference between yields on 10-year Treasury note and 1-year Treasury note), changes in FED interest rate (the effective Federal Fund rate) and changes in Default spread (the difference between yields on Moody's BAA-rated and AAA-rated corporate bonds).[5] Since these variables are highly persistent, their changes are close to estimated surprises. The macroeconomic variables are obtained from the Federal Reserve H.15 data library. Among some of the empirical papers using these variables see Hahn and Lee (2006); Petkova (2006); Campbell and Vuolteenaho (2004); Bali and Engle (2010). Summary statistics of the risk factors are provided in Table 1.

3.3 Information Variables

State variables such as those discussed earlier are potential proxies for intertemporal risk as they are likely correlated to assets that help in offsetting the risk from changing investment opportunities. Therefore they are also useful to investors for learning about the economy and making forward-looking investment decisions. For conditioning information, we use the lagged information from two types of variables that we lag and demean for estimation (see Figure 8). We use bond related variables such as Default spread, Term Spread and change in risk free rate (as defined earlier).[6] We also use stock related variables, such as the excess US market dividend yield and the US market realized volatility. The US market dividend yield and realized market volatility are calculated from the daily returns of the CRSP value-weighted market index.[7] We demean all variables for estimation (see Figure 8). The macroeconomic variables are from

[5] Merton also lists other potential candidates for the intertemporal risk factor, such as shifts in the wage-rental ratio, and inflation. However, we failed to find reliable time series for these variables with weekly frequency.
[6] To facilitate the interpretation of the changes in the risk free rate we also provide the plot of the level of one month T-bill rates in Figure 8.
[7] To compute weekly dividend yield we use the two series of annualized market returns from the previous year, including distributions and excluding distributions, at the weekly frequency. The dividend yield is calculated from the difference between the two return series, divided by the value of the index excluding distributions. Realized Volatility for each week is computed as the square root of the sum of daily squared market return of that week, multiplied by the trading days of the year and then divided by the trading days of the week.

Federal Reserve H.15 data library and the market data are from CRSP. Although the selection can often seem ad-hoc, these variables are commonly applied and have the support of the predictability literature (see among others: Keim and Stambaugh (1986); Campbell (1987); Fama and French (1989); Campbell and Shiller (1988); Fama and Schwert (1977)).

4 Empirical Results

4.1 Estimating time-varying risk

In this paper we implement the ADCC proposed by Cappiello, Engle, and Sheppard (2006), where we allow for a leverage effect in the variance dynamic through GJR-GARCH and asymmetry in correlation (Longin and Solnik (2001), Ang and Bekaert (2002)) to capture higher comovements in market downturns that are at times associated with recessions. Consistent with the GARCH literature, the parameter estimates of the ADCC specification are highly significant.[8] The average of the estimate for the persistence of the univariate volatility specification, β, is 0.86 and the coefficients are significant at 1 percent confidence level for all assets in the cross section. The average of α is 0.04 with the variance stationary condition holding for all assets. The results show supportive evidence in favor of asymmetric volatility. The average value of the δ parameters is 0.12 and the coefficients are significant at 5 percent for 30 out of the 31 total assets in the cross section. Similarly, the persistence parameter for the correlations, b, is 0.92 on average and is highly significant in the cross section. The results also bring supportive evidence in favor of asymmetric correlations, albeit with weaker statistical significance since the parameter for correlation asymmetry, g, is only significant for half of the asset pairs. The estimated correlations of industry portfolios with the market portfolio are indeed higher during recession periods, when most market downturns occur. The cross-sectional average of the conditional correlations is 0.78 in recessions and 0.74 expansions.

Table 2 provides summary statistics on the conditional covariances computed from the ADCC filter between asset pairs and market risk, as well as the proxies of intertemporal risk. On average, assets show larger covariance with the market portfolio and lower covariance with the bond portfolio. The average of the conditional covariances with the market is 4.84 and 0.08 with

[8] To save space these estimations are not reported but are available upon request from the authors.

the bond returns. Those with the change in Federal Reserve fund rate and change in Default premium are negative whereas the average of the covariances with the change in Term Premium is positive. Among all risk factors, the covariances of asset returns with the Term Premium have the largest standard deviation at 6.27 and the covariances with the Bond have on average the lowest volatility.

4.2 Unconditional model

We start with presenting results of the unconditional models for the ICAPM under different specifications. In addition to market risk, the intertemporal risk factor is proxied either through the composite returns from the aggregation of three bonds with maturity over ten years, or the innovations to three macro-economic variables as described in the state variable data section, either one at a time or together. This unconditional analysis is also helpful to compare our results to previous papers and to establish a benchmark for the rest of the analysis. The evidence is in Table 3. The price of market risk is positive and significant, with point estimates in a range between 0.78 to 1.06 among all models, while the model intercept is never significant. In non-tabulated results, we run regressions with a similar specification for the risks but with asset specific intercepts. In those instances, a test for their significance fails to reject the null that they are joint zero. We then add the intertemporal risk through the bond returns and we find a negative price of risk that is significant in our test, in contrast with the evidence in Scruggs and Glabadanidis (2003) and tests reported by Gerard and Wu (2006). Thus increasing the cross-section of assets adds power to the test and allows us to identify the long-term bond as a potential proxy for intertemporal risk. When we proxy the intertemporal risk using the innovations in the macro-variables one at a time, the evidence shows a significant price for the Default Premium and the FED rate but not for the Term Premium. Furthermore, only the one linked to the FED rate survives when we consider all the innovations in the same regression. The positive sign of the coefficient combined with a negative conditional covariance is indication that this proxy has particular hedging value for investors. Overall the sign of the coefficient for the proxies in combination with their conditional covariance is consistent with the sign of market predictive regressions, as argued by Maio and Santa-Clara (2012) for tests of the ICAPM in the cross-section.

It is important to point out that including the intertemporal factors does not change the statistical significance of the market price of risk in all the ICAPM regressions, although in most cases the estimated price is actually lower than in the one-factor model. This is at odd with the expectations that the price of market risk would be biased downward when omitting other priced factors that can be negative based on the theory. Our coefficient on the market risk return tradeoff is also lower than the one reported in Bali (2008). However we find that our estimate would be in line with his magnitude when using as in that paper, a cross-section that excludes the market portfolio.

4.3 Dummy specification

Our first approach to investigate risk prices through the business cycle is to estimate the specification in equation (2) where IV_t consists of a constant and a dummy variable that switches on at the weeks corresponding to the NBER recessions. If the risk-return trade-off is to be linked to the risk aversion of investors and if the expected reward for risk is changing with fluctuations in the economy, then we would expect a positive coefficient for market risk. Furthermore, if the intertemporal risk is driven by state variables that should help in hedging shifts in the investment opportunity set, then we would also expect to see a significant change in the price attached to at least some of our proxies. We estimate a fully specified model that also adds the recession dummy for the intercept. Including this dummy might seem in contradiction with the hypothesis that we are testing, that changes in the business cycle should be modifying the marginal impact of time-varying risk on expected returns, rather than affecting the average of the excess returns. However we acknowledge that there could be factors that are missing from our empirical model, and thus omitting the intercept dummy would bias the estimates of our parameters of interest whenever that coefficient is different from zero.

The results from this analysis are in Table 4. The price of market risk is again positive and is somewhat higher than the unconditional evidence presented in Table 3 with a range between 1.17 and 1.31. The dummy variable for the price of market risk across the single and multi-factor models is more often negative than positive, however it is never significant. Only the price from the proxy for the change in the Federal Fund rate is significant outside recessions but not affected by them. Similarly, we find no evidence of impact from recessions on the price for any other proxy for the change in investment opportunities. While we find that the intercept is not significant in the unconditional regression, the point estimate for the intercept conditional on recessions is larger than the one in the unconditional regression across all the models. Furthermore, through the significance of the intercept dummy, we find that there is a sizable change in returns associated with the recession periods that cannot be explained by changes in neither market nor intertemporal risk.

An asset pricing model that is specified according to the theory should not include an intercept, either constant or time-varying. Thus as a check we estimate a model with no intercept and another with no dummy for the intercept. The magnitude of the prices of risk outside the recession periods are in a range than is similar to the prices for the dummy model of table 4, while their associated dummies are larger by an order of magnitude, always negative for all different risk specifications, but never significant. The results are not qualitatively different for the model with no intercept, except for the market price of risk that is somewhat larger, in a range between 1.25 and 1.42 (results available from the authors).

4.4 Specifications with business cycle information

4.4.1 Moving Window estimation

There are a few potential explanations for the results of the dummy interaction model, not mutually exclusive. It is possible that there is an additional risk that we are not estimating and that is not correlated with the ones that we are specifying. We might have too few recession weeks (13.3% of the sample period). It might be the case that the methodology does not have power to distinguish between the regimes. On the other hand a moving window estimation of the model shows that during recessions the price of market risk increases.

Figure 1 plots the price of market risk obtained from a one-year moving window estimation of the one factor CAPM and of the ICAPM with Macro Risk. Each price of market risk shown in the plot corresponds to the result of the previous 52-observation estimation, which we then smooth with a Hodrick-Prescott filter for better examination. The NBER recession periods are marked by green bars on the plot. The choice of one year window is motivated by the average duration of the recessions in our sample (51.6 weeks per recession). Based on this, the estimates in the plot immediately after the recession bars correspond to the price of market risk during a recession period. In all asset pricing specifications the price of market risk corresponding to the recession periods increases in magnitude comparing to the adjacent point estimate that lacks recession observations. On average the size of the coefficient for the price of market risk estimated for the ICAPM with Macro Risk is larger than the other cases.[9]

Besides the widely discussed shortcomings in characterizing the dynamics in real time, the moving window approach is very sensitive to the choice of the estimation window and is also not able to reliably convey information on the precision of the estimates. Indeed with a moving window estimation performed with these parameters, the power of the estimator is inevitably lower than an estimation that makes use simultaneously of all the available observations in our sample. We thus turn to a model where the time-variation in the compensation for risks is not based on ex-post information through a dummy but rather is related to conditioning variables linked to business cycle fluctuations.

4.4.2 One information variable

We now estimate the case where the IV_t in equation (3) includes either a single continuous variable or a set of variables. The results are in Table 5. The top panel reports the results from the one-factor CAPM model, the middle panel has the results of the ICAPM that uses the composite aggregate long maturity bond returns as a proxy for the shift in the investment opportunities, the last panel shows the ICAPM with innovations in the three macro-variables. In all panels, the regressions analyze the significance of one conditioning information variable at a time. Table 6 has them all together and is discussed in the following section. We report individual coefficients and their unconditional standard errors plus a number of joint tests. For example, in panel A, for each regression we report two p-values, one for the joint significance of the intercept coefficients, the other one for the joint significance of the risk price coefficients. If all $\lambda_i = 0$, then the covariances with the risk factors do not help in explaining the expected returns. The t-test for significance on the loadings for the information variables instead provides information on whether there is time-variation in the mean (intercept coefficient) or in the

[9] The average price of market risk from the ICAPM with Macro Risk is 8.26, 6.47 for the one-factor CAPM and 5.70 for the ICAPM with Bond Risk

relationship with the conditional covariances (prices of risk coefficients). Given that our information variables are demeaned for regression estimation, the constant coefficient on the conditional risk is for the marginal effect of time-varying risk when all $IV_t = 0$, thus for values of the information (state) variables when the economy is most likely not at a peak or a trough of the cycle. In other words, it is not capturing the average relationship between covariance risks and expected returns independently from the state of the economy, as in the case for the unconditional specification of Table 3. Panels B and C contain information that is similarly organized, including tests for the additional intertemporal risk factors.

We first discuss the results on the market price of risk. Based on the t-tests on the individual coefficients the evidence on time variation throughout the cycle is quite strong. The p-values of the joint Wald tests on market risk indicate that the conditioning information is statistically significant in modifying the relationship between time-varying risk and expected returns. We find that there is significant time-variation associated with almost all the information variables, except for the default premium where it is not very robust. In the case of the realized volatility, we see that it modifies the relationship only in periods of heightened uncertainty, since the information variable is not significant at the average for market risk in all three panels. The conclusion on the pricing of market risk is consistent across the one factor and the different multi-factor candidate models. Overall the results on the market are in line with the evidence presented by other papers that use similar empirical pricing models but different methodologies to uncover the significance of the information variables. The evidence on the time-variation and on the joint significance for the potential proxies for intertemporal risk is more mixed. Statistical significance is quite limited when we consider the average of the long maturity bonds. There is instead some support for time-variation and pricing for the macro-risks, especially for the innovations in the risk free rate, and for those in the default premium, with low p-values for three out of five information variables. Among the information variables, the three with high persistence are overall more consistently significant across all the risk proxies.

The individual t-tests and the joint Wald tests on the risk coefficients reported in Table 5 provide a gauge of the level of uncertainty in the unconditional estimation. In other words, they are unconditional tests of a conditional relation and therefore they are not helping in identifying under what conditions, that is, at what level of the information variables the relationship is significant. However it is useful to learn when and how the reward to risk changes, conditional on the changes in the economy that investors can infer from the information available. Thus to go beyond what can be learned though the tables of coefficients, we turn to an illustration of the risk-return tradeoff. This analysis can also be revealing if one is looking into distinguishing the different role of market and intertemporal proxies in compensating for risk at different stages of the economic cycle.

4.4.3 Illustration of the risk-return trade-off through the business cycle

In Figure 2 we depict the risk-return trade-off, i.e. the marginal effect of the time-varying market (covariance) risk on expected returns, for the range of the conditioning variables. For each time-varying information variable we plot on the y-axis the estimated price of market risk based on values of the conditional variable on the x-axis. The plots also report the 95 percent conditional confidence intervals to help in assessing the values for which the association is statistically significant. We can thus shed light on the changes in the price of risk through different economic conditions. In other words, in this analysis we look at when and how the reward to risk changes with the conditioning information.

The plots in Figure 2 are an illustration of the coefficient for market risk from Table 5, panel A when we look at the effect of conditioning using one information variable at a time.[10] The plots show that the price of market risk is positive when the conditioning variable is zero, thus under "normal" (i.e. average) economic conditions, or within the cycle, and it is significant at that value for all the information variables except the realized volatility. For example, when the conditioning variable is zero, we find a point estimate of 0.49 for the default premium, that is shown as significant in Table 5, and whose conditional confidence intervals exclude zero in the corresponding plot of the figure. This implies that the default premium is modifying the relationship between time-varying risk and expected returns in an average stage of the economic cycle.

In the case of the excess dividend yield, the term premium and the default premium, the slope of the price of market risk is positive, thus it is increasing from values below to values above the average of the conditioning variable, i.e. from the left to the right on the x-axis. These three variables have a different range over our sample period but for all three, a negative reading

[10] This analysis follows the suggestions in Brambor, Clark, and Golder (2006).

occurs before a recession, while a positive reading that follows a negative one is indication that a recession has ended. To go back to the example of the default premium, the slope coefficient is significant at the 5 percent for values above zero and the positive (0.64) number is indicating that the price is increasing through values often associated with a deteriorating economy. This suggests that investors require positive and increasing compensation to accept market risk as the economy moves toward and through a downturn and decreasing compensation when the default premium is decreasing, that is often the case after a recession. Thus the conditional risk-return relation helps generate time-varying increasing market risk premia through recessions.

For the excess dividend yield and the term premium the plots also show a negative and significant price of risk for values approximately below -2, when the confidence intervals exclude zero. The frequency of a negative significant estimate for the price of risk is respectively 20 percent and 10 percent when we condition on these two variables. This is more than what could be attributed to chance, however only 3.2 and 4.6 percent of the time sample falls within the region of significance. This range of values is achieved during the high inflation period of 1979-1982 with the change in monetary policy during Chairman Volcker, a quite unusual time. It is not surprising that this methodology that keeps a linear price of market risk cannot always preserve the price to be positive, in line with what economic theory indicates. However it is reassuring to verify that in case of the other three conditioning variables, we never have instances of an estimated price of market risk that is negative and significant.

The evidence is mixed when we look at the marginal impact from covariances with intertemporal risk, conditional on one information variable at a time. As indicated in Table 5, Panel B, we find no significance for any range of values of the information variables when we proxy intertemporal risk with the bond returns of long maturities. The evidence in Panel C is more encouraging in the case of the innovations in the three macro-risk proxies. In Figure 3 we observe that the conditional price of intertemporal risk proxied by the innovations in the risk-free rate is positive at the zero average and significant for most of the information variables, as indicated by the constant coefficients in panel C. In the case of all the three highly persistent information variables, the slope coefficients are significant and negative, with an opposite dynamics than those of the conditional price of market risk. The price of intertemporal risk is thus higher before a recession and lower at the end, and then increasing under the opposite economic cycle. This finding seems to support the view of a hedging component linked to intertemporal risk when proxied by a variable like the changes in the risk free rate that negatively predicts market returns. Differently from the price for market risk, these dynamics generate risk premia that are pro-cyclical, rather than counter-cyclical. Risk-averse investors would in fact require less compensation from assets that deliver a higher payoff in bad states of the economy. In addition, the plots reveal that these prices are statistically significant mainly over the negative range of the information variables, thus when it is likely that a recession has begun following a period of economic expansion. In the case of the market risk, these same information variables are instead significant mainly over the positive range, thus following a recession into the expansion.

As illustrated in Figure 4 when we use the innovations in the default premium as proxy for intertemporal risk, the marginal impact on expected returns from the time-varying risk is actually increasing with larger (increasingly positive) values of the excess dividend yield and of the term premium, similar to the evidence for the price of market risk. In Figure 5, the price proxied by the innovations in the Term Premium is significant only when conditioning on the default premium, where the evidence is qualitatively similar to that from the reward to market risk, with a price that is lower at the beginning and higher at the end of a recession. Given that both the default premium and the term premium predict market returns with a positive sign, this result suggests that assets positively correlated with innovations in these two proxies cannot provide hedging value in downturn. For these proxies the required reward to intertemporal risk is reinforcing the counter-cyclical pattern observed for market risk. There are however differences as to when we detect significance in figure 4 and 5 from what we show in figure 2 for market risk. The conditional confidence intervals cover mainly the negative range of the information variables, thus at the beginning of the recession, rather than afterwards.

The interpretation of the negative slope for the changes in the risk free is analogous, bearing in mind that values below zero and increasingly negative are associated with easing cycles in monetary policy, likely in recessions. As shown in Figure 2, the price of market risk is positive and significant at the average of the variable, corresponding to the coefficient 0.91 of table 5. With a slope coefficient of -0.91, the price is still significant, and becomes positive for range of values of the changes in the risk free rate from zero and below. As in the case of the previous three conditioning variables, this points to an expected compensation for market risk that is increasing while the economy is contracting and decreasing while the economy is expanding. In

Figure 4, the behavior in the price of intertemporal risk proxied with the default premium has similar dynamics with the risk free rate as information variable, albeit with lower statistical significance. We also check the robustness of this result if we use the level of interest rates rather than the changes (results not tabulated). The evidence is qualitatively similar, also indicating that the expected compensation of risk is increasing when the level of interest rate is decreasing below the average.

The plot of the realized volatility in Figure 2 through 4 reveals that investors require positive and increasing compensation with larger (positive) values of the variable. While realized volatility is most commonly associated with dynamics of the stock market at higher frequency, Campbell et al. (2001) shows that market volatility is strongly related to downturns in the economic cycle. The estimates of the regression indicate that the change in the marginal impact from covariance risk due to market volatility is positive, confirming our intuition that investors require increasing compensation to accept more risk during periods of higher volatility that are often associated with recessions. This is statistically significant for market risk and for intertemporal risk when proxied by state variables that positively predict the market.

4.4.4 All information variables

Table 6 reports coefficients on the asset pricing models when we condition on information from all the variables in the same regression. The table reports individual coefficients and associated unconditional standard errors, plus two joint Wald tests for each risk of the models in panel A, B and C. The first Wald test is similar to the one in Table 5 for the joint significance of the price coefficients (or those of the intercept) over the whole range of values. The second one is a joint test for the significance of time-variation when the information variables are not at a zero. The joint Wald tests indicate that unconditionally we can reject that the time-varying relationship between the risks and expected returns is zero. This relationship is significant for market covariance risk at any significance level. It is also highly supported for the covariances with two of the macro proxies and marginally for those with the long maturity bond and the change in term premium. These statistics offer us an unconditional assessment of the importance of time-variation.

When we condition on all variables in the same regression, the marginal impact of a change in covariance risk on expected returns is more difficult to evaluate. We start by comparing the results of each regression coefficients in this table with those in the single conditioning variable regressions of Table 5. We observe that among the coefficients that explain the risk-return trade-off for the market, those for the term and the default premium switch sign. This pattern is common to the one risk factor, the long maturity composite bond and the multi–macro intertemporal risk models and it indicates, perhaps not surprisingly, that when we condition on all the information variables, it is harder to disentangle the contribution of each. The correlation among the information variables is particularly high between the excess dividend yield and the term premium on the one side and the default premium and the realized volatility on the other side. This can provide an explanation for the changing slopes and also points to the challenges of interpreting empirical evidence when there is no clear prediction from the theory.

To better understand the evidence on the combined role of the time-varying information variables both in economic and statistical terms, it is more useful to turn to the plots of the time-varying prices of risks in Figures 6 and to the summary statistics of Table 7. In Figure 6 the estimated conditional prices together with their conditional confidence intervals are shown in the common time domain rather than for range of values that are different for each conditioning variable. Panel A presents the time-varying price of market risk together with the H-P filtered representation below. The bars mark the recession periods. Conditioning on multiple time-varying variables still preserves the upward slope of changes in price, from the start of recession periods following through its ending. Since the quantity of market risk is positive as indicated in Table 2, the linear regression model is able to estimate counter-cyclical market risk premia for the large cross-section of assets. Except for the period 1982-1992, the price of risk is positive and statistically significant in the period after a recession. As also shown by the plots of Figure 2, we have instances where the price of risk is negative, due to the linear specification for the price in the regression, and statistically significant. Panel B contains the time-varying prices for intertemporal risk as proxied by the innovations in the macro variables. The plots of the prices show that intertemporal risk is significantly priced in both recessions and expansions. In most of the instances of recessions, it is evident that the price of intertemporal risk is larger at the beginning and decreases through the trough when proxied by the changes in the risk free rate, the state variable that is negatively related to future market returns.

More information on what is depicted in these figures is in Table 7, where we report summary statistics for the conditional time-varying prices. Next to each price we also report the number of weeks as a percentage of the total weeks in our sample when the estimated price is significant, based on the conditional standard errors. Thus we provide more precise inference on the behaviour of the prices of risk by combining the estimation uncertainty of the regression coefficients with the variability of the information variable at each time *t*.

First, we present the statistics for the price of market risk estimated in all three models. A number of comments are in order. The average of the price of market risk is positive across all models, but unlike the unconditional regressions of Table 3 we find that it is larger in the case of the ICAPM with three Macro risks. A one-sided test for difference in means between the series of the estimated prices rejects that its market price is smaller than the price of the one-factor only in the case of the ICAPM specification with macro risks.[11] Taking into account the values of the conditioning variables in quantifying uncertainty shows that the estimated price of risk is significant at the 5 percent in approximately 70 percent of the weeks, and around 50 percent when we consider only the weeks where the price is positive. When we look separately at the weeks in expansion (2350) and in recession (361), the proportion of time when the market price is significant does not substantially change in the expansionary periods (in a range of 48 to 50 percent), but it is halved for the recession weeks.

Now consider the evidence on the four proxies of intertemporal risk. The average of the time-varying prices is not substantially different in magnitude than the estimates of the unconditional regressions but in this case it is also positive for the bond and for the change in the default premium. The significance at each *t,* thus conditional on the level of the time-varying variables, is overall lower that what the Wald tests of Table 6 indicate for all the four proxies, and more so for the proxy with the long-maturity composite bond and the one with the innovations in the term premium. However the prices of intertemporal risk are still quite informative, performing relatively better than the market price at characterizing changes in risk over recessions. This is more evident in the case of the innovations in the risk free rate, with significance in 58 percent of recession weeks versus 37 percent of expansion weeks. With a similar pattern, in non-tabulated results, we find that the percentage of weeks when at least one of the three macro proxies for intertemporal risk is larger for recessions (81 percent) than

[11] The tests are performed with Newey-West standard errors. Similar tests for the economic significance reject the null that the prices are zero for all specifications.

expansions (71 percent). While we find no substantial differences among the p-values of the Wald tests obtained from the regressions in Table 6, the conditional confidence intervals prove to be quite useful, despite the noise introduced by the time-variation in the conditioning information. Through them, we can effectively distinguish the different roles of market and intertemporal risk and highlight the importance of the estimated prices of inter-temporal risk over the economic cycles.

Differently from the evidence provided by the dummy model, these results indicate that even within a linear regression approach, the specification with the information variables has some success in identifying significant changes linked to the business conditions. In summary, we find that differences in the prices of market and intertemporal risk are heightened in recessions. The expected compensation for market risk increases, while there is statistical support for the fact that investors are willing to accept lower compensation for risk from those assets correlated with macro-economic state variables that negatively predict market returns. The higher statistical significance of intertemporal risk in recessions suggests that this risk becomes in those times a much larger component of total premia also in economic terms.

4.4.5 Abnormal returns and inter-temporal risk

As empirical papers have often attributed the evidence of abnormal returns in a one-factor model to an unspecified missing factor that could be related to intertemporal risk, in this section we shed some light on this issue.

While the results of the unconditional model show insignificant estimates for the asset specific intercepts, the regressions presented in Table 4 find that the intercept changes significantly, possibly with changes in the economic conditions. The specification of regression (2) allows us to separate the time-variation in risks from the unexplained time-variation with the help of the estimated time-varying intercepts in the conditional models. The p-values on the Wald tests in the regressions of Table 5 indicate weak statistical significance for the time-varying intercept only through the Term Premium information variable. However, when we pool all the information variables, the evidence in Table 6 indicates some differences with respect to the intercept between the one-factor model and those models with intertemporal risk. In the case of the one-factor model of Panel A the intercept test rejects that there is no residual time-variation throughout the cycles, from recessions and expansions. Similarly, De Santis and Gerard (1997) and Gerard and Wu (2006) find predictability in the residuals from a conditional CAPM, in case of both a model with constrained and one with unconstrained price of market risk. On the other hand, the models with intertemporal risk of Panel B and C represent an improvement with respect to these statistics, especially in the case of the model with intertemporal risk proxied by the long maturity bond. In Table 7 we provide statistics for the time-varying intercept estimated from the state variables for the three candidate models. We also include the percentage of weeks when the intercept is significant based on the conditional confidence intervals and the difference in recession and expansion periods. While we see no substantial difference in the summary statistics, we do find that including intertemporal risk in the asset pricing model reduces the frequency when the abnormal return is statistically significant from 22 to 15 percent of weeks.

Figure 7 provides additional insights on the behavior of the time-varying intercepts in conjunction with the dynamics of the price of market risk. On the top panel we plot the difference between the time varying intercept of the ICAPM model with Macro risks from that of the one-factor CAPM. Similarly, in the bottom panel we plot the difference in the prices of market risk between the two models. On the plot, NBER recession periods are marked by bars. From the upper plot it is evident that decreases in the difference between the intercepts occur in correspondence of recessions. In the lower plot we see that the ICAPM fits a price of market risk that is larger in magnitude, an indication that the one-factor CAPM price of market risk is downward biased possibly from the omission of other risk factors. Moreover we see that the difference between the estimates of the price of risk in the two models widens during recessions, with the price of the multi-factor model becoming even larger in those weeks. Thus for the ICAPM, the decrease in the intercept shown in the upper plot, cannot be explained by its price of market risk becoming smaller, but rather by the other factors that are capturing more of the time-variation in those times.[12]

One concern about the evidence on the relative significance of the price of market risk in recessions versus expansions could be the unequal size of the time sample. In our sample, recession periods include almost eight times fewer observations than expansion periods, (361 to 2350 observations). To control for this, we perform a simple simulation experiment where we

[12] The two other spikes in the difference between the estimated prices of market risk correspond to the stock market crash in 1987 and the euro sovereign debt crisis.

first match the recession and expansion periods synthetically and then compute the summary statistics of the prices as in Table 7. More specifically, we randomly draw 361 samples without substitution from the estimated price of market risk from the pool of 2350 observations in expansion periods, in order synthetically to generate an expansion time series with identical number of observations as the recession. In the next step, we calculate the percent of significant and positive weeks of the price of market risk for that draw, similar to Table 7. This experiment is run for 1000 times. The average percent of the results shows that in 49.11% of the expansion periods the price of market risk is statistically significant and positive. Hence, the simulation experiment confirms the results of Table 7, removing the concern that results in this table are driven by differences in sample sizes.

To sum up, this analysis suggests that the price of market risk is downward biased without intertemporal risk factors. Moreover, the difference is heightened during recession periods when the unexplained time-variation of the ICAPM model also decreases. Thus a model with intertemporal risk is able to better explain conditional time-variation in recessions.

5 Robustness checks

5.1 Alternative Methodology

The two-step estimation of the asset pricing model has a number of advantages. It enables us to increase the cross-section of assets while overcoming issues with dimensionality, it helps in evaluating the importance of multiple distinct sources of risks, and it allows to easily derive conditional confidence intervals because of the linearity of the parameters in estimation. These advantages represent a step forward from a simultaneous one-step approach but come with a trade-off. In equation (1) expected returns are conditional on information at time t and thus their empirical representation in equation (2) would require for all elements of the risk premia to be function of the conditioning variables. The methodology that we implement separates the conditional analysis. We first obtain estimates of time-varying quantities of risks under the simplifying assumption that the covariances with the risk factors depend only on their own lagged values, rather than both lagged values and the investors' information set. The regression with interaction then conditions the prices of risk on the information available at time t in the asset-pricing step. While we have strong statistical support also for the lagged covariances, it is difficult to say to what extent the information in the variables rather than that in own lags is important in describing the conditional relation, given that such variables are in fact proxies with some predictive power. To ease concerns with our approach, we estimate in one-step the specification (2) with the standard multivariate GARCH-in-Mean methodology proposed by De Santis and Gerard (1997). Their approach needs a number of simplifying assumptions to alleviate the curse of dimensionality but even with these restrictions estimating the full ICAPM model with several risk factors is still numerically challenging.[13] Thus we estimate the model for the simplest case, i.e. the one- factor CAPM with constant or with time-varying price of risk and no intercept. In this setting the price of risk, λ_t, and the covariance matrix, H_t, are estimated simultaneously and are thus both function of the conditioning variables and lagged covariances. First, we find that the conditional covariances estimated with a constant or time-varying price of risk are remarkably similar to the estimates of our two-step methodology in terms of level and variability, although the test for equality between the series rejects. The one-step (two-step) price has a mean and a standard deviation of 0.63 (0.65) and 3.82 (2.88) respectively and a test with Newey-West standard errors cannot reject with a p-value of 0.94 equality in the mean of the series of the one-step and two-step time-varying prices. Many of the individual coefficients for the price are significant in the three-step regression but not in the one-step estimation. Thus simultaneously estimating a larger number of coefficients for time-variation in both prices and quantities of risk reduces the precision of the estimates. We also compare the estimates of the exponential price of risk from the one-step methodology that imposes the non-negativity restriction with that of the linear price of risk from the three-step methodology. In correspondence to periods when the linear price of risk is negative, the exponential price specification fits a price that is almost zero in magnitude.

5.2 Alternative specifications for conditional second moments

Bali and Engle (2010) implement a different specification for the correlation dynamics, a symmetric matrix DCC with time-invariant price of risk. As this specification accounts for no

[13] De Santis and Gerard (1997) estimate a vector version instead of the full matrix version for the GARCH dynamic parameters and impose a covariance stationarity assumption to further reduce the number of parameters in estimation.

asymmetric patterns in volatilities and in correlation, estimating a matrix, instead of a single scalar for each parameter of the correlation dynamics is numerically less complicated. As a robustness check, we implement this alternative specification, and augment it with the interaction model described in the previous section. Similar to the GARCH-in-Mean methodology we estimate the one-factor CAPM with time-varying price of risk, time-varying market risk and no intercept. We find that the size and significance level of the parameter estimated are comparable with the ADCC specification complemented with interactions that we implement in this paper.

5.3 Alternative Risk Factors

Proxying intertemporal risk through a different bond index or with individual macro risk factors one at a time does not qualitatively change our results. We estimate the ICAPM with bond risk from returns on the average of all CRSP Treasury bonds. The results of the unconditional and conditional estimations are reported in Table 8 and show that the magnitude and t-stats of the estimated parameters is comparable with the estimation results of the ICAPM with Long term bonds. Table 8 also has estimates of the ICAPM with only one of the macro risk factors and provides evidence that the results of the three macro risks are not driven by the correlation among these factors. Indeed the table shows that the magnitude and t-stats of the estimated parameters for each factor is comparable with the estimation results of the ICAPM with three macro risks.

6 Conclusion

We use linear regressions to investigate in an asset pricing model how the time-variation in the prices of risk is related to the business cycle. Our model specification is intertemporal as we account for multiple sources of risk through the innovations in state variables, and also conditional as the time-varying prices of the different risks are functions of lagged variables in the information set of investors. For each asset we first obtain estimates of time-varying quantities of risk under the simplifying assumption that the conditional covariances with the risk factors depend only on their own lagged values. These estimates are our regressors when we pool the time-series and cross-section of the assets in panel regressions. By combining these two dimensions we gain power in testing the cross-sectional restrictions for the prices of risk.

Confirming the evidence in previous literature, we find that the price of market risk is significantly time-varying. In addition, our conditional analysis shows that the price is increasing with dynamics in the information variables that accompany recession periods and is decreasing for dynamics in those variables associated with expansions. In other words, the reward for taking on market risk increases during recessions. We further provide new evidence on intertemporal risk, whose prices are also found to be significantly time-varying in the case of most of the state variables that we use to proxy for shifts in the investment opportunity set. Differently from the price of market risk, we find that for the proxy that negatively predicts market returns the reward for intertemporal risk is decreasing with dynamics for the information variables that are associated with recessions. This is consistent with the expectations that these proxies should provide hedging value in bad states of the economy and thus investors are willing to accept lower compensation as the likelihood of a downturn increases.

In addition to displaying how the different prices of risk change, our analysis also establishes when they are more important relative to each other. For this purpose, we construct the time t *conditional* confidence intervals based on the values of the information variables through the business cycles. We are then able to show that in statistical terms, the price of intertemporal risk proxied by the innovations in the risk free rate is more significant relatively to the price of market risk in recessions. Furthermore, the unexplained time-varying component of the asset pricing model also substantially decreases during recessions in the case of the intertemporal CAPM. The higher statistical significance of intertemporal risk in recessions suggests that in those periods this risk becomes a much larger component of total premia also in economic terms. These findings can be useful for asset management, given that asset allocation should be affected by changes in investors' expected compensation for risk.

References

Ang, Andrew, and Geert Bekaert, 2002, International Asset Allocation with Regime Shifts, *The Review of Financial Studies* 15, 1137–1187.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *The Journal of Finance* 61, 259–299.

Bali, Turan G., 2008, The intertemporal relation between expected returns and risk, *Journal of Financial Economics* 87, 101–131.

Bali, Turan G., and Robert F. Engle, 2010, The intertemporal capital asset pricing model with dynamic conditional correlations, *Journal of Monetary Economics* 57, 377–390.

Bollerslev, Tim, and Jeffrey M. Wooldridge, 1992, Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, *Econometric Reviews* 11, 143–172.

Brambor, Thomas, William Roberts Clark, and Matt Golder, 2006, Understanding Interaction Models: Improving Empirical Analyses, *Political Analysis* 14, 63–82.

Brennan, Michael J., Ashley W. Wang, and Yihong Xia, 2004, Estimation and Test of a Simple Model of Intertemporal Capital Asset Pricing, *The Journal of Finance* 59, 1743–1775.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.

Campbell, John Y., 1993, Intertemporal Asset Pricing without Consumption Data, *The American Economic Review* 83, 487–512.

Campbell, John Y., João Cocco, Francisco Gomes, Pascal J. Maenhout, and Luis M. Viceira, 2001, Stock Market Mean Reversion and the Optimal Equity Allocation of a Long-Lived Investor, *European Finance Review* 5, 269–292.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad Beta, Good Beta, *The American Economic Review* 94, 1249–1275.

Campbell, J. Y., and R. J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–228.

Cappiello, Lorenzo, Robert F. Engle, and Kevin Sheppard, 2006, Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns, *Journal of Financial Econometrics* 4, 537–572.

Chen, Long, and Xinlei Zhao, 2009, Return Decomposition, *Review of Financial Studies* 22, 5213–5249.

Daniel, Kent, and Sheridan Titman, 2012, Testing Factor-Model Explanations of Market Anomalies, *Critical Finance Review* 1, 103–139.

De Santis, Giorgio, and Bruno Gerard, 1997, International Asset Pricing and Portfolio Diversification with Time-Varying Risk, *The Journal of Finance* 52, 1881–1912.

Engle, Robert F., and Kevin Sheppard, 2001, Theoretical and Empirical properties of Dynamic Conditional Correlation Multivariate GARCH. Working Paper, National Bureau of Economic Research.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

Fama, Eugene F., and G.William Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115–146.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The Variation of Economic Risk Premiums, *Journal of Political Economy* 99, 385–415.

Gerard, Bruno, and Guojun Wu, 2006, How Important Is Intertemporal Risk for Asset Allocation?, *The Journal of Business* 79, 2203–2241.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *The Journal of Finance* 48, 1779–1801.

Guo, Hui, and Robert Savickas, 2008, Average Idiosyncratic Volatility in G7 Countries, *Review of Financial Studies* 21, 1259–1296.

Guo, Hui, and Robert F. Whitelaw, 2006, Uncovering the Risk-Return Relation in the Stock Market, *The Journal of Finance* 61, 1433–1463.

Hahn, Jaehoon, and Hangyong Lee, 2006, Yield Spreads as Alternative Risk Factors for Size and Book-to-Market, *Journal of Financial and Quantitative Analysis* 41, 245–269.

Hansen, Lars Peter, 1982, Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica* 50, 1029–1054.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357–390.

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

Longin, François, and Bruno Solnik, 2001, Extreme Correlation of International Equity Markets, *The Journal of Finance* 56, 649–676.

Maio, Paulo, and Pedro Santa-Clara, 2012, Multifactor models and their consistency with the ICAPM, *Journal of Financial Economics* 106, 586–613.

Merton, Robert C., 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica* 41, 867–

887.

Ozoguz, Arzu, 2009, Good Times or Bad Times? Investors' Uncertainty and Stock Returns, *Review of Financial Studies* 22, 4377–4422.

Petkova, Ralitsa, 2006, Do the Fama–French Factors Proxy for Innovations in Predictive Variables?, *The Journal of Finance* 61, 581–612.

Scruggs, John T., and Paskalis Glabadanidis, 2003, Risk Premia and the Dynamic Covariance between Stock and Bond Returns, *The Journal of Financial and Quantitative Analysis* 38, 295–316.

Whitelaw, R. F., 2000, Stock market risk and return: an equilibrium approach, *Review of Financial Studies* 13, 521–547.

A. Asymmetric Dynamic Conditional Correlation

For the estimation of the conditional second moments, we implement the Asymmetric Dynamic Conditional Correlation (ADCC) specification proposed by Cappiello, Engle, and Sheppard (2006). ADCC enables us to capture the asymmetric dynamics both in volatility and in correlations.[14]

Formally, we first take out any autoregressive elements in the returns of each asset and filter them with a univariate asymmetric GARCH model (Glosten, Jagannathan, and Runkle (1993)):

$$\begin{aligned} R_t &= \phi_0 + \phi_1 R_{i,t-1} + u_t, \qquad\qquad u_t \sim N(0, \sigma_t) \\ \sigma_t^2 &= \omega + \beta\, \sigma_{t-1}^2 + (\alpha + \delta I[u_{t-1} < 0])\, u_{t-1}^2 \end{aligned}$$

Where, $I(\cdot)$ denotes the indicator function; ϕ_0, ϕ_1 are the autoregressive coefficients; ω, α, β are the GARCH parameters; δ captures the "leverage effect". In this setting σ_t^2 denotes the conditional variance of assets, derived by conditioning on the previous assets' returns.

In the second step we compute estimates of the bivariate conditional correlations between each asset return and the market portfolio, with a scalar ADCC filter. Concatenate standardized return of asset i and market portfolio to form matrix $\boldsymbol{\varepsilon_t}$ and set $\bar{\rho} = E[\boldsymbol{\varepsilon_t \varepsilon_t'}]$ the unconditional correlation of asset pairs. Then the 2×2 Matrix $\boldsymbol{\rho_t}$ below generates the conditional correlations between each asset pair.

$$\begin{aligned} Q_t &= \; (\bar{\rho} - \mathrm{a}^2\bar{\rho} - \mathrm{b}^2\bar{\rho} - \mathrm{g}^2\bar{N}) \; + \; a^2 \boldsymbol{\varepsilon_{t-1}\varepsilon_{t-1}'} \; + \; \mathrm{g}^2 n_{t-1} n_{t-1}' \; + \; b^2 Q_{t-1} \\ \boldsymbol{\rho}_t &= \; diag(Q_t)^{-\frac{1}{2}} \; Q_t \; diag(Q_t)^{-\frac{1}{2}} \end{aligned}$$

Here, $n_t = I[\boldsymbol{\varepsilon}_t < 0] \,.\!*\, \boldsymbol{\varepsilon_t}$, where $I(\cdot)$ denotes the indicator function and $.*$ denotes the Hadamard or element by element matrix multiplication. A necessary and sufficient condition for Q_t to be positive definite is that $\mathrm{a}^2 + \mathrm{b}^2 + \delta \mathrm{g}^2 < 1$, where $\delta = \max(eigenvalue[\bar{\rho}^{-\frac{1}{2}} \bar{N} \bar{\rho}^{-\frac{1}{2}}]$.

As the assumption of conditional normality is often violated in stock returns, in both steps we

[14] Volatility of a firm may increase after a negative shock due to effects like leverage effect or volatility feedback. Leverage of a firm (debt-to-equity ratio) increases after a negative shock to the stock value. Thus, the volatility of the whole firm, which is assumed to remain constant, must be reflected by an increase in volatility in the non-leveraged part of the firm (equity). Similarly correlations may increase following negative systematic shocks that induce downward pressure on returns of any pairs of stocks.

use the Quasi-Maximum Likelihood Estimator (QMLE) that is consistent and asymptotically normal. For multivariate GARCH models, Bollerslev and Wooldridge (1992) show that this estimator is consistent as long as the first two moment equations are correctly specified. After estimating the conditional correlations, we compute the variance-covariance matrix of assets, $D_t \boldsymbol{\rho}_t D_t$, choosing D_t as a diagonal matrix of conditional standard deviations with $\sigma_{i,t}$ and $\sigma_{m,t}$ on the diagonal and zeroes elsewhere.

B. Parks Estimator[15]

Once conditional covariances are computed with the ADCC, we estimate the coefficients of the asset pricing model conditioning on a set of information variables in a panel regression. Since stock returns have high contemporaneous cross correlations, we implement Parks estimator, a GLS estimator for the panel regression, that not only corrects for heteroskedasticity and autocorrelation in the error terms, but also takes into account the cross correlations in the error terms.

Consider a system of N equations, of which the typical i^{th} equation is

$$y_i = X_i \beta_i + \varepsilon_i,$$

where y_i is a $T \times 1$ vector of time-series observations on the ith dependent variable, X_i is a $T \times k_i$ matrix of observations of k_i independent variables, β_i is a $k_i \times 1$ vector of unknown coefficients to be estimated, and ε_i is a $T \times 1$ vector of random disturbance terms with mean zero. Parks (1967) proposes an estimation procedure that allows the error term to be both serially and cross-sectionally correlated. In particular, he assumes that the elements of the disturbance vector ε follow an AR(1) process:

$$\varepsilon_{i,t} = \rho_i \varepsilon_{i,t-1} + u_{i,t}, \quad u_{i,t} \sim N(0, \phi_{ii})$$

And ε_i are contemporaneously correlated, i.e. $E(\varepsilon_{i,t}\varepsilon_{j,t}) = \sigma_{ij}$ and $E\left(\varepsilon_{i,t}\varepsilon_{j,s}\right) = 0, \quad (t \neq s)$.

He suggests the following steps to estimate β in a GLS procedure:

1. Run OLS regression on all observations pooled, i.e stack all y_i in a vector to get a

[15] From the book of Elements of Econometrics by Jan Kmenta (Page 512).

vector Y (with size of $N.T \times 1$) and stack matrix X_i similarly. Then run the OLS estimation and obtain residuals$e_{i,t}$.

2. Estimate an AR(1) process on the residuals, i.e. regress $e_{i,t}$ time series on lagged residuals to obtain $\hat{\rho}_i$
3. Correct the autocorrelation of the dependent variables and transform Y and X to Y^* and X^* as following. Note that we lose 1 observation here and Y^* and X^* have $N(T-1)$ observations,

$$Y_{i,t}^* = Y_{i,t} - \hat{\rho}_i Y_{i,t-1}$$

4. Run OLS estimation on Y^* and X^* and obtain transformed residual $u_{i,t}^*$
5. Compute the covariance matrix Ω

$$\hat{\phi}_{i,j} = \frac{1}{T-k-1} \sum_{t=2}^{T} u_{i,t}^* u_{j,t}^*$$

$$s_{i,j} = \frac{\hat{\phi}_{i,j}}{1-\hat{\rho}_i \hat{\rho}_j}$$

note $\hat{\phi} = \frac{1}{T-k-1} (u^*)^T u^*$

$$\tilde{\beta} = (X^T \widehat{\Omega}^{-1} X)^{-1} X^T \widehat{\Omega}^{-1} Y$$

with

$$\text{Asympt. Var} - \text{Cov}(\tilde{\beta}) = (X^T \widehat{\Omega}^{-1} X)^{-1}$$

where,

$$\Omega = \begin{bmatrix} \sigma_{11} P_{11} & \sigma_{12} P_{12} & \cdots & \sigma_{1N} P_{1N} \\ \sigma_{21} P_{21} & \sigma_{22} P_{22} & \cdots & \sigma_{2N} P_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1} P_{N1} & \sigma_{N2} P_{N2} & \cdots & \sigma_{NN} P_{NN} \end{bmatrix}$$

$$P_{ij} = \begin{bmatrix} 1 & \rho_j & \cdots & \rho_j^{T-1} \\ \rho_i & 1 & \cdots & \rho_j^{T-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_i^{T-1} & \rho_i^{T-2} & \cdots & 1 \end{bmatrix}$$

$s_{i,j}$ and $\hat{\rho}_i$ are consistent estimates of $\sigma_{i,j}$ and ρ_i

6. we can also use the simplified version form Aitken's estimator

$$\tilde{\beta} = ((X^*)^T \hat{\Phi}^{-1} X^*)^{-1}((X^*)^T \hat{\phi}^{-1} Y^*)$$

with

$$\text{Asympt. Var} - \text{Cov}(\tilde{\beta}) = ((X^*)^T \hat{\Phi}^{-1} X^*)^{-1}$$

$$\hat{\Phi} = \hat{\phi} \otimes I_{T-1}$$

note that $\hat{\Phi}^{-1} = \hat{\phi}^{-1} \otimes I_{T-1}$ which is numerically useful in computing the inverse matrix.

C. Interaction models and conditional variances

Filtering the price of risks with interaction models would involve estimating the system below, assuming a one factor asset pricing model:

$$R_{i,t} - R_{f,t} = \beta_0 + \beta_1 cov_{t-1}(R_{i,t}, R_{m,t}) + \beta_2\ \mathrm{IV}_{t-1} + \beta_3\ \mathrm{IV}_{t-1} cov_{t-1}(R_{i,t}, R_{m,t}) + \epsilon_{i,t} \qquad \text{(C.1)}$$

In this setting conditional price of market risk, λ_t, is the derivative of the left hand side with respect to the regressand. Thus we have:

$$\lambda_t = \left(\frac{\partial R_i}{\partial cov}\middle| IV\right) = \beta_1 + \beta_3 IV$$
$$var\left(\frac{\partial R_i}{\partial cov}\middle| IV\right) = var(\beta_1) + IV^2 var(\beta_3) + 2IV cov(\beta_1, \beta_3)$$

(C.2)

Conditioning is done on a set of K information variables, $IV = [IV_1, \ldots, IV_{\mathrm{K}}]$. As a results we have $\beta_3 = [\beta_{3,1}, \ldots, \beta_{3,\mathrm{K}}]$. So the extended version of the above formula becomes:

$$\begin{aligned} var\left(\frac{\partial R_i}{\partial cov}\middle| IV\right) = {} & var(\beta_1) + IV_1 cov(\beta_1, \beta_{3,1}) + \cdots + IV_{\mathrm{L}} cov(\beta_1, \beta_{3,\mathrm{K}}) \\ & + IV_1 cov(\beta_{3,1}, \beta_1) + IV_1^2 var(\beta_{3,1}) + \cdots + IV_1 IV_L cov(\beta_{3,1}, \beta_{3,L}) \\ & + \cdots \\ & + IV_{\mathrm{L}} cov(\beta_{3,K}, \beta_1) + IV_{\mathrm{L}} IV_1 cov(\beta_{3,\mathrm{K}}, \beta_{3,1}) \ldots + IV_{\mathrm{L}}^2 var(\beta_{3,K}) \end{aligned}$$

Table 1

The table reports summary statistics for the test assets, the state variables risk proxies in the asset pricing models and the information variables. Panel A reports mean, standard deviation, minimum and maximum of excess returns of the 30 Industry portfolios in percentage, as well as their autocorrelations and correlations with state variables. Panel B reports the summary statistics for the state variables. We use the average of CRSP Treasury bond returns for maturities over 10-years, the changes in the Term Premium, Default Premium and effective Federal Funds rate as proxies for intertemporal risk. Panel C provides summary statistics on excess market dividend yield, Term Premium, Change in Risk Free rate, Default Premium and Realized market volatility that we use as conditioning information variables. The data are obtained from Kenneth French online data library and the Federal Reserve Library for the period of January 1962 to December 2013.

Panel A

	I. Summary Statistics				II. AutoCorrelations			III. Correlations				
	Mean	Std	Min	Max	Lag 1	Lag 4	Lag 12	market	10 Yr+ Bonds	Δ TP	Δ DP	Δ FED
Food Products	0.136	2.044	-14.784	15.594	0.01	-0.01	0.01	0.76	0.10	0.06	0.03	-0.04
Beer & Liquor	0.147	2.554	-17.374	14.083	-0.02	-0.02	-0.03	0.62	0.10	0.03	0.01	-0.05
Tobacco Products	0.194	3.069	-18.086	25.157	-0.03	-0.05	0.02	0.51	0.09	0.02	0.03	-0.02
Recreation	0.134	3.423	-24.191	31.823	0.05	0.03	0.00	0.81	-0.03	0.04	-0.03	-0.02
Printing and Publishing	0.103	2.734	-19.465	23.676	0.06	0.00	0.00	0.83	0.01	0.06	0.00	-0.02
Consumer Goods	0.107	2.420	-25.191	18.154	-0.05	-0.06	0.01	0.75	0.10	0.03	0.01	-0.02
Apparel	0.128	2.886	-18.362	18.946	0.10	0.01	-0.02	0.79	-0.01	0.07	0.00	-0.03
Health	0.136	2.483	-17.531	18.982	-0.01	-0.02	-0.01	0.79	0.09	0.04	0.00	-0.01
Chemicals	0.117	2.750	-18.304	15.418	0.01	-0.01	-0.02	0.83	-0.06	0.09	-0.03	-0.02
Textiles	0.131	3.204	-23.931	27.740	0.11	0.01	0.00	0.71	-0.05	0.07	-0.04	-0.02
Construction	0.111	2.905	-18.969	31.528	0.04	-0.01	-0.04	0.86	-0.01	0.07	-0.01	-0.01
Steel	0.065	3.527	-26.390	29.621	0.01	-0.02	-0.04	0.79	-0.12	0.10	-0.05	-0.02
Fabricated Products	0.116	2.915	-23.081	18.811	0.05	0.00	-0.01	0.89	-0.10	0.08	-0.03	0.00
Electrical Equipment	0.171	3.070	-19.760	15.293	0.00	-0.02	-0.03	0.85	-0.01	0.06	-0.02	-0.02
Automobiles	0.093	3.212	-21.972	28.972	0.03	0.03	-0.01	0.77	-0.05	0.07	-0.04	-0.02

Table 1 Panel A continued

Aircraft, ships, railroad	0.154	2.986	-23.908	15.004	0.04	0.01	-0.02	0.79	-0.01	0.05	-0.02	0.00
Mines	0.103	3.526	-24.308	26.274	0.04	0.03	-0.02	0.55	-0.09	0.09	-0.04	-0.01
Coal	0.192	4.740	-27.271	33.558	-0.01	0.04	0.00	0.56	-0.10	0.08	-0.06	-0.01
Oil and Gas	0.153	2.758	-25.967	13.725	-0.05	-0.02	0.01	0.70	-0.06	0.06	-0.02	-0.01
Utilities	0.085	1.923	-20.881	13.441	0.05	0.00	0.00	0.67	0.14	0.07	0.05	-0.04
Telecom	0.092	2.326	-20.960	16.801	-0.04	0.01	-0.02	0.76	0.08	0.07	0.02	-0.03
Services	0.131	2.962	-22.512	14.483	0.10	-0.02	0.01	0.88	-0.01	0.05	-0.01	-0.03
Business Equipment	0.105	3.309	-23.374	18.933	0.01	-0.03	0.01	0.84	-0.05	0.04	-0.02	-0.01
Paper	0.106	2.442	-20.199	16.688	0.03	-0.01	-0.02	0.84	-0.01	0.06	-0.01	-0.03
Transportation	0.121	2.829	-22.210	13.740	0.04	-0.01	-0.03	0.83	-0.01	0.06	-0.01	-0.03
Wholesale	0.123	2.551	-17.833	11.443	0.11	0.01	-0.03	0.85	0.00	0.05	-0.03	-0.05
Retail	0.133	2.620	-16.955	13.935	0.02	-0.01	-0.01	0.84	0.04	0.06	0.01	-0.03
Meals	0.149	2.917	-16.011	18.889	0.06	0.01	0.02	0.76	0.05	0.05	0.02	-0.03
Ficials	0.114	2.729	-21.451	26.354	0.00	0.00	-0.05	0.88	0.04	0.09	0.02	-0.01
Other	0.064	2.640	-18.869	18.103	0.06	0.02	-0.02	0.81	0.01	0.06	0.00	-0.03
market	0.099	2.195	-18.339	13.342	0.01	-0.02	-0.01	1.00	0.01	0.07	-0.01	-0.02

Table 1 continued

Panel B

	I. Summary Statistics				II. Autocorrelations			III. Correlations				
	Mean	Std	Min	Max	Lag 1	Lag 4	Lag 12	market	10 Yr+ Bonds	Δ TP	Δ DP	Δ FED
market	0.201	2.194	-18.319	13.468	0.01	-0.02	-0.01	1				
10 Yr+ Bonds	0.134	1.287	-5.226	10.302	-0.01	0.03	0.00	0.01	1			
Δ TP	0.001	0.119	-0.920	1.000	0.30	0.10	0.04	0.07	-0.06	1		
Δ DP	0.000	0.053	-0.370	0.490	0.27	0.06	0.01	-0.01	0.18	0.10	1	
Δ FED	-0.001	0.301	-2.440	2.890	-0.07	0.17	-0.08	-0.02	-0.05	-0.31	-0.04	1

Panel C

	I. Summary Statistics				II. AutoCorrelations			III. Cross Correlations				
	Mean	Std	Min	Max	Lag 1	Lag 4	Lag 12	xDY	TP	Δ Rf	DP	Realized Vol
xDY	-2.281	2.664	-12.847	2.732	0.99	0.95	0.89	1				
TP	0.995	1.171	-3.250	3.470	0.99	0.96	0.88	0.67	1			
Δ Riskfree	-0.001	0.398	-5.720	4.524	0.00	-0.18	0.00	-0.08	-0.07	1		
DP	1.029	0.458	0.310	3.470	0.99	0.96	0.86	-0.14	0.18	-0.05	1	
Realized Vol	5.644	4.025	0.395	63.040	0.65	0.51	0.33	0.05	0.10	-0.02	0.34	1

Table 2

The table reports summary statistics for the conditional covariances of the test assets with the risk factors. Risk factors are average of CRSP Treasury bond returns over 10 years maturities, changes in the Term Premium, Default Premium and effective Federal Funds rate. Conditional covariances are from weekly returns (in percentage) and calculated through the Asymmetric Dynamic Conditional Correlation (ADCC) methodology.

	Cov (Ri, Market)				Cov (Ri, 10+ Bonds)			
	Mean	Std	Min	Max	Mean	Std	Min	Max
Food Products	3.497	4.463	-0.875	75.798	0.322	0.790	-3.904	5.625
Beer & Liquor	3.549	3.461	-0.875	38.291	0.380	0.624	-1.316	2.823
Tobacco Products	3.478	2.837	0.812	31.715	0.385	0.602	-1.318	2.836
Recreation	6.081	8.576	1.381	124.044	0.081	1.227	-10.969	5.662
Printing and Publishing	4.943	6.733	1.143	97.136	0.162	1.037	-6.336	4.000
Consumer Goods	4.146	4.789	0.373	63.102	0.339	0.722	-2.590	4.412
Apparel	5.000	5.903	1.111	67.879	0.079	0.982	-5.820	4.215
Health	4.436	5.126	1.093	83.944	0.296	0.737	-2.660	4.867
Chemicals	5.037	6.212	0.572	84.703	-0.059	1.268	-9.349	3.283
Textiles	4.935	7.301	0.659	92.384	-0.010	0.992	-7.241	2.964
Construction	5.544	7.510	0.810	101.002	0.130	1.274	-8.502	3.802
Steel	5.953	8.134	1.027	123.159	-0.369	1.650	-11.202	3.252
Fabricated Products	5.754	7.593	1.118	106.744	-0.158	1.325	-9.834	2.919
Electrical Equipment	5.680	6.492	1.389	88.054	0.086	1.247	-7.678	3.178
Automobiles	5.367	7.050	0.729	105.910	-0.057	1.353	-9.030	3.147
Aircraft, ships, railroad	5.217	5.808	0.791	77.449	0.043	1.086	-5.913	3.072
Mines	3.852	5.620	-0.512	78.259	-0.346	1.283	-8.586	3.945
Coal	5.260	7.523	0.356	93.524	-0.358	1.729	-12.053	3.046
Oil and Gas	4.193	5.549	-0.067	93.472	-0.076	0.954	-5.877	1.908
Utilities	2.823	4.062	0.478	78.675	0.417	0.760	-2.793	3.736
Telecom	3.859	5.142	0.664	84.677	0.287	1.048	-5.855	4.139
Services	5.785	6.549	1.378	80.691	0.056	1.127	-6.139	3.503
Business Equipment	6.146	7.040	1.500	79.436	-0.043	1.140	-6.556	3.424
Paper	4.517	5.356	0.744	75.917	0.063	0.930	-4.694	3.008
Transportation	5.207	5.938	1.318	81.784	0.073	1.036	-6.196	3.339
Wholesale	4.907	5.997	0.769	87.311	0.114	1.008	-6.130	5.605
Retail	4.884	5.586	1.021	74.823	0.220	0.925	-4.438	5.640
Meals	4.887	5.102	1.170	60.178	0.210	0.913	-4.114	4.221
Financials	5.326	7.403	1.041	107.340	0.284	1.310	-9.310	4.258
Other	4.634	5.205	0.442	64.736	0.177	0.936	-4.470	3.397
market	5.117	6.800	1.235	112.969	0.154	1.038	-7.096	4.978

Table 2 continued

	Cov (Ri, Δ TP)				Cov (Ri, Δ DP)				Cov (Ri, Δ FED)			
	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
Food Products	1.290	5.377	-13.426	61.059	0.160	1.156	-17.086	6.209	-0.856	4.237	-27.088	36.568
Beer & Liquor	0.606	4.866	-14.829	44.545	0.054	0.698	-6.845	4.002	-1.534	2.365	-26.074	28.603
Tobacco Products	0.267	4.502	-7.611	35.060	0.082	0.827	-7.685	3.372	0.071	0.705	0.000	16.665
Recreation	1.558	7.007	-24.709	57.137	-0.504	3.177	-55.781	3.497	0.514	3.252	-1.763	126.751
Printing and Publishing	1.401	6.846	-24.806	53.969	-0.181	3.095	-47.994	5.307	-0.488	2.438	-5.393	54.598
Consumer Goods	0.912	5.024	-19.666	41.241	0.017	0.914	-11.581	4.863	-0.715	1.826	-15.179	57.064
Apparel	2.130	5.398	-19.649	36.225	-0.222	1.220	-18.034	2.665	-0.745	2.939	-19.423	31.262
Health	0.917	5.452	-22.743	50.205	-0.227	1.353	-24.160	3.843	0.476	3.548	-12.712	38.036
Chemicals	2.357	7.386	-29.030	52.944	-0.717	2.430	-35.949	3.865	0.708	2.712	-21.518	73.180
Textiles	2.519	7.264	-25.253	53.610	-0.564	1.555	-25.829	0.473	0.643	2.828	-7.385	127.933
Construction	2.050	8.186	-36.404	64.463	-0.359	2.480	-38.330	3.760	0.832	2.658	-16.438	91.987
Steel	3.729	8.592	-19.099	71.574	-1.033	3.556	-52.979	1.174	0.797	0.891	0.022	24.108
Fabricated Products	2.394	6.953	-34.591	54.369	-0.519	3.015	-52.201	2.997	1.587	2.242	-8.109	64.423
Electrical Equipment	1.705	6.198	-32.249	40.355	-0.390	1.967	-34.527	3.551	-0.120	2.934	-40.010	80.028
Automobiles	2.455	6.758	-16.277	46.623	-0.610	3.398	-54.160	5.782	0.407	2.832	-14.286	104.785
Aircraft, ships, railroad	1.654	6.257	-28.729	43.737	-0.204	1.585	-22.327	3.047	-0.727	3.372	-21.279	16.873
Mines	3.368	5.407	0.085	51.087	-0.614	1.890	-28.678	0.474	1.508	2.439	0.036	30.562
Coal	3.318	6.619	-2.397	47.692	-1.181	3.092	-44.686	0.644	-0.708	5.026	-39.509	27.876
Oil and Gas	1.255	3.586	-13.166	30.460	-0.579	2.291	-38.715	2.110	0.048	1.880	-25.892	34.726
Utilities	0.956	6.419	-33.247	59.825	0.233	1.529	-22.872	8.134	-0.755	0.958	-5.964	24.635
Telecom	1.615	5.157	-24.361	51.216	-0.164	2.489	-39.765	5.230	-1.047	1.181	-6.126	16.236
Services	1.518	6.807	-40.592	55.359	-0.152	1.392	-24.160	3.818	0.405	2.043	-14.439	15.046
Business Equipment	1.132	5.597	-30.185	37.346	-0.447	1.984	-32.103	3.642	0.571	4.837	-19.482	33.165
Paper	1.585	6.447	-38.180	50.478	-0.305	1.591	-23.856	4.511	-0.529	2.226	-6.685	84.572
Transportation	1.600	6.494	-42.984	50.920	-0.264	0.627	-12.924	1.353	-0.098	5.326	-26.456	29.645
Wholesale	1.516	5.703	-30.246	45.507	-0.303	1.920	-32.257	3.724	-1.018	2.128	-8.369	53.173
Retail	1.668	5.784	-21.052	46.706	-0.026	1.398	-20.269	5.181	-0.607	2.318	-7.296	36.831
Meals	1.602	6.266	-18.233	54.822	0.093	1.264	-16.641	4.927	-0.073	4.565	-30.283	25.483
Financials	2.441	8.882	-31.520	74.078	-0.210	2.968	-47.967	6.432	-0.515	1.916	-4.838	57.481
Other	1.860	7.021	-27.531	62.508	-0.193	1.450	-21.392	4.457	-1.278	4.751	-32.693	36.811
market	1.575	6.209	-30.528	56.317	-0.258	2.383	-43.085	6.129	-0.122	3.492	-21.854	26.976

Table 3

The table reports coefficients of the asset pricing models, assuming constant prices of risk during the sample period. The market model assumes that $\gamma_j = 0$. The t-stats are reported in parenthesis and statistical significance levels at 10%, 5%, and 1% are indicated by *,**,*** respectively.

$$R_{i,t} - R_{f,t-1} = \alpha + \lambda\, Cov_{t-1}(R_{i,t}, R_{m,t}) + \sum_{j=1}^{L} \gamma_j\, Cov_{t-1}(R_{i,t}, z_{j,t}) + \epsilon_{i,t}$$

	α *100	λ	γ	γ	γ	γ
	intercept	market	10+ Bonds	Δ TP	Δ DP	Δ FED
	0.01	1.03***				
(1)	(0.2)	(4.15)				
	0.01	0.88***	-3.42**			
(2)	(0.41)	(3.56)	(-2.24)			
	0.01	1.06***		-0.36		
(3)	(0.28)	(4.25)		(-1.61)		
	0.02	0.78***			-1.26**	
(4)	(0.48)	(2.82)			(-1.97)	
	0.02	1.05***				0.69***
(5)	(0.75)	(4.21)				(4.28)
	0.03	0.85***		-0.24	-1.05	0.67***
(6)	(0.98)	(3.04)		(-1.04)	(-1.63)	(4.15)

Table 4

The table reports coefficients of the asset pricing models conditional on NBER recession periods, assuming constant prices of risk during the sample period. The dummy variable D in the model gets a value of 1 during NBER recessions and zero otherwise. The market model assumes $\gamma_0 = \gamma_1 = 0$. The t-stats are reported in parenthesis and statistical significance levels at 10%, 5%, and 1% are indicated by *,**,*** respectively.

$$R_{i,t} - R_{f,t-1} = \alpha + \lambda\, Cov_{t-1}(R_{i,t}, R_{m,t}) + \sum_{j=1}^{L} \gamma_j\, Cov_{t-1}(R_{i,t}, z_{j,t}) + \epsilon_{i,t}$$

$$\alpha = \alpha_0 + \alpha_1 D$$

$$\lambda = \lambda_0 + \lambda_1 D$$

$$\gamma_j = \gamma_{0,j} + \gamma_{1,j} D$$

	α0 *100 intercept	λ0 market	γ0 10+Bonds	γ0 Δ TP	γ0 Δ DP	γ0 Δ FED	α1 *100 intercept	λ1 market	γ1 10+Bonds	γ1 Δ TP	γ1 Δ DP	γ1 Δ FED
	0.03	1.19***					-0.31***	-0.02				
(1)	(0.99)	(3.3)					(-3.27)	(-0.04)				
	0.04	1.27***	-2.71				-0.28***	-0.20	-0.78			
(2)	(1.25)	(3.5)	(-1.49)				(-2.89)	(-0.39)	(-0.22)			
	0.03	1.19***		-0.22			-0.30***	0.02		-0.19		
(3)	(1.01)	(3.29)		(-0.67)			(-3.21)	(0.04)		(-0.43)		
	0.04	1.24***			-1.96		-0.30***	-0.21			1.18	
(4)	(1.18)	(3.36)			(-1.48)		(-3.09)	(-0.36)			(0.75)	
	0.05	1.17***				0.49**	-0.28***	0.03				0.33
(5)	(1.45)	(3.21)				(2.26)	(-2.98)	(0.06)				(100)
	0.06*	1.23***		-0.16	-1.82	0.49**	-0.28***	-0.02		-0.07	1.40	0.28
(6)	(1.65)	(3.3)		(-0.5)	(-1.37)	(2.24)	(-2.91)	(-0.03)		(-0.16)	(0.89)	(0.83)

Table 5

The table reports coefficients of the asset pricing models conditional on information variables, assuming time-varying prices of risk during the sample period. Each column reports the estimation of the asset pricing model, conditional on only one information variable. Panel A reports the estimations for the one-factor CAPM, Panel B reports the estimation of the ICAPM with Bond risk and Panel C reports the estimation of the ICAPM with three Macro Risk. The market risk model assumes $\boldsymbol{\gamma} = \mathbf{0}$. At the bottom of each panel, we report the p-value of the null hypothesis of zero price of risk. The t-stats are reported in parenthesis and statistical significance levels at 10%, 5%, and 1% are indicated by *,**,*** respectively.

$$R_{i,t} - R_{f,t-1} = \alpha_{t-1} + \lambda_{t-1} Cov_{t-1}(R_{i,t}, R_{m,t}) + \gamma_{t-1,j}\, Cov_{t-1}(R_{i,t}, z_{j,t}) + \epsilon_{i,t}$$
$$\alpha_{t-1} = \boldsymbol{\alpha}'\, IV_{t-1}$$
$$\lambda_{t-1} = \boldsymbol{\lambda}'\, IV_{t-1}$$
$$\gamma_{t-1,j} = \boldsymbol{\gamma}'\, IV_{t-1}$$

Panel A

Conditional Estimates	**IVt**	**xDY**		**TP**		**Δ Rf**		**DP**		**realized Vol**	
Intercept *100	**Constant**	-0.01	(-0.2)	0.00	(0.00)	0.01	(0.17)	0.01	(0.45)	0.02	(0.57)
	xDY	0.01	(0.71)								
	TP			0.05*	(1.72)						
	Δ Rf					-0.10	(-1.32)				
	DP							0.06	(0.81)		
	realized Vol									-0.01	(-0.81)
Market	**Constant**	0.49*	(1.96)	0.59**	(2.33)	0.91***	(3.66)	0.49*	(1.68)	0.44	(1.2)
	xDY	0.60***	(7.68)								
	TP			1.05***	(5.44)						
	Δ Rf					-0.98**	(-2.25)				
	DP							0.64**	(2.4)		
	realized Vol									0.05***	(2.71)
$\text{p} - \text{value H}_0\text{: Joint Wald of } \alpha_t = 0$		0.48		0.09		0.19		0.42		0.42	
$\text{p} - \text{value H}_0\text{: Joint Wald of } \lambda_t = 0$		0.00		0.00		0.02		0.02		0.01	

Table 5 continued

Panel B											
Conditional Estimates	**IVt**	**xDY**		**TP**		**Δ Rf**		**DP**		**realized Vol**	
Intercept *100	**Constant**	-0.02	(-0.48)	0.00	(-0.04)	0.01	(0.34)	0.02	(0.53)	0.02	(0.64)
	xDY	0.01	(1.05)								
	TP			0.05*	(1.72)						
	Δ Rf					-0.11	(-1.37)				
	DP							0.07	(0.95)		
	realized Vol									-0.01	(-0.73)
Market	**Constant**	0.42	(1.56)	0.58**	(2.19)	0.74***	(2.96)	0.44	(1.5)	0.27	(0.74)
	xDY	0.67***	(7.67)								
	TP			1.02***	(5.05)						
	Δ Rf					-1.12**	(-2.34)				
	DP							0.53	(1.62)		
	realized Vol									0.05***	(2.73)
Long Term Bond	**Constant**	3.88**	(2.19)	-0.79	(-0.45)	-3.59**	(-2.34)	-3.00*	(-1.67)	-2.11	(-1.2)
	xDY	-0.56	(-1.14)								
	TP			0.05	(0.04)						
	Δ Rf					0.97	(0.37)				
	DP							0.26	(0.1)		
	realized Vol									-0.15	(-1.18)
$\mathrm{p-value\ H_0:\ Joint\ Wald\ of}\ \alpha_t = 0$		0.29		0.086		0.17		0.343			0.46
$\mathrm{p-value\ H_0:\ Joint\ Wald\ of}\ \lambda_t = 0$		0.00		0.000		0.02		0.10			0.01
$\mathrm{p-value\ H_0:\ Joint\ Wald\ of}\ \gamma Bond_t = 0$		0.25		0.971		0.71		0.92			0.24

Table 5 continued

Panel C											
Conditional Estimates	**IVt**	**xDY**		**TP**		**Δ Rf**		**DP**		**realized Vol**	
Intercept *100	**Constant**	0.00	(-0.02)	-0.01	(-0.25)	0.03	(0.88)	0.05*	(1.69)	0.05	(1.45)
	xDY	-0.01	(-0.9)								
	TP			0.02	(0.83)						
	Δ Rf					-0.06	(-0.76)				
	DP							0.09	(1.2)		
	realized Vol									-0.01	(-0.91)
Market	**Constant**	1.33***	(4.56)	1.07***	(3.7)	0.62**	(2.18)	0.63**	(2.05)	0.37	(0.97)
	xDY	0.80***	(7.71)								
	TP			1.24***	(5.26)						
	Δ Rf					-1.05**	(-2.29)				
	DP							0.67	(1.59)		
	realized Vol									0.08***	(3.65)
Δ TP	**Constant**	-0.02	(-0.09)	0.32	(1.34)	-0.20	(-0.87)	-0.82***	(-2.75)	-0.39	(-1.42)
	xDY	-0.04	(-0.81)								
	TP			-0.08	(-0.64)						
	Δ Rf					-0.23	(-0.96)				
	DP							0.72**	(2.56)		
	realized Vol									0.04*	(1.8)
Δ DP	**Constant**	1.03	(1.31)	-1.93**	(-2.51)	-1.25*	(-1.93)	-0.97	(-0.77)	-2.81***	(-2.99)
	xDY	0.85***	(4.77)								
	TP			3.20***	(5.82)						
	Δ Rf					-2.43*	(-1.83)				
	DP							0.63	(0.74)		
	realized Vol									0.18***	(3.61)
Δ FED	**Constant**	0.23	(1.33)	0.15	(0.82)	0.63***	(3.82)	0.78***	(4.22)	0.67***	(3.66)
	xDY	-0.19***	(-4.82)								
	TP			-0.61***	(-5.36)						
	Δ Rf					-0.03	(-0.16)				
	DP							-0.47**	(-2)		
	realized Vol									-0.01	(-0.29)
$\mathrm{p-value\ H_0}$: Joint Wald of $\alpha_t = 0$		0.37		0.41		0.45		0.23		0.36	
$\mathrm{p-value\ H_0}$: Joint Wald of $\lambda_t = 0$		0.00		0.00		0.02		0.11		0.00	
$\mathrm{p-value\ H_0}$: Joint Wald of $\gamma\Delta TP_t = 0$		0.42		0.52		0.34		0.01		0.07	
$\mathrm{p-value\ H_0}$: Joint Wald of $\gamma\Delta DP_t = 0$		0.00		0.00		0.07		0.46		0.00	
$\mathrm{p-value\ H_0}$: Joint Wald of $\gamma\Delta FED_t = 0$		0.00		0.00		0.87		0.05		0.78	

Table 6

The table reports coefficients of the asset pricing models conditional on all information variables, assuming time-varying prices of risk. Panel A reports the estimations of the one-factor CAPM, Panel B reports the estimation of the ICAPM with Bond risk and Panel C reports the estimation of the ICAPM with Macro risk. The market risk model assumes $\boldsymbol{\gamma} = \mathbf{0}$. At the bottom of each panel, we report the p-values for the null hypothesis of zero prices of risk as well as the null hypothesis of constant prices of risk. The t-stats are reported in parenthesis and statistical significance levels at 10%, 5%, and 1% are indicated by *,**,***

$$R_{i,t} - R_{f,t-1} = \alpha_{t-1} + \lambda_{t-1} Cov_{t-1}(R_{i,t}, R_{m,t}) + \sum_{j=1}^{L} \gamma_{t-1,j}\, Cov_{t-1}(R_{i,t}, z_{j,t}) + \epsilon_{i,t}$$
$$\alpha_{t-1} = \boldsymbol{\alpha}'\, IV_{t-1}$$
$$\lambda_{t-1} = \boldsymbol{\lambda}'\, IV_{t-1}$$
$$\gamma_{t-1,j} = \boldsymbol{\gamma}_{\boldsymbol{j}}'\, IV_{t-1}$$

		Panel A		Panel B		Panel C	
Conditional Estimates	**IVt**						
Intercept*100	**Constant**	-0.01	(-0.32)	-0.03	(-0.98)	0.02	(0.74)
	xDY	-0.02	(-1.16)	-0.01	(-0.59)	-0.03*	(-1.71)
	TP	0.07*	(1.88)	0.06	(1.57)	0.07	(1.63)
	Δ Rf	-0.10	(-1.31)	-0.12	(-1.39)	-0.07	(-0.86)
	DP	0.14*	(1.79)	0.10	(1.2)	0.13	(1.6)
	realized Vol	-0.02*	(-1.83)	-0.01*	(-1.67)	-0.02**	(-1.99)
Market	**Constant**	0.61	(1.59)	0.54	(1.32)	0.95**	(2.17)
	xDY	1.17***	(7.15)	1.36***	(7.56)	1.25***	(6.39)
	TP	-0.77**	(-2.12)	-1.05***	(-2.76)	-0.78*	(-1.85)
	Δ Rf	-0.56	(-1.26)	-0.62	(-1.27)	-0.52	(-1.07)
	DP	-2.06***	(-4.99)	-2.24***	(-4.79)	-1.37**	(-2.32)
	realized Vol	0.07***	(3.11)	0.07***	(3.26)	0.09***	(3.39)
Long Term Bond	**Constant**			2.99	(1.42)		
	xDY			-2.39***	(-3)		
	TP			4.51**	(2.06)		
	Δ Rf			1.44	(0.53)		
	DP			2.15	(0.86)		
	realized Vol			-0.11	(-0.69)		
Δ TP	**Constant**					-0.61*	(-1.69)
	xDY					-0.03	(-0.25)
	TP					-0.32	(-1.19)
	Δ Rf					-0.14	(-0.57)
	DP					0.87**	(2.47)
	realized Vol					-0.01	(-0.36)
Δ DP	**Constant**					2.59*	(1.79)
	xDY					0.21	(0.6)
	TP					2.91***	(2.75)
	Δ Rf					-2.34*	(-1.69)
	DP					-3.31***	(-2.98)
	realized Vol					0.14**	(2.05)
Δ FED	**Constant**					0.23	(0.95)
	xDY					-0.20**	(-2.53)
	TP					-0.06	(-0.29)
	Δ Rf					-0.15	(-0.65)
	DP					-1.11***	(-3.68)
	realized Vol					0.04*	(1.71)

Table 6 continued

	Panel A	Panel B	Panel C
p − value H_0: Joint Wald of $\alpha_t = constant$	0.02	0.08	0.04
p − value H_0: Joint Wald of $\alpha_t = 0$	0.02	0.10	0.06
p − value H_0: Joint Wald of $\lambda_t = constant$	0.00	0.00	0.00
p − value H_0: Joint Wald of $\lambda_t = 0$	0.00	0.00	0.00
p − value H_0: Joint Wald of $\gamma Bond_t = constant$		0.09	
p − value H_0: Joint Wald of $\gamma Bond_t = 0$		0.04	
p − value H_0: Joint Wald of $\gamma \Delta TP_t = constant$			0.05
p − value H_0: Joint Wald of $\gamma \Delta TP_t = 0$			0.09
p − value H_0: Joint Wald of $\gamma \Delta DP_t = constant$			0.00
p − value H_0: Joint Wald of $\gamma \Delta DP_t = 0$			0.00
p − value H_0: Joint Wald of $\gamma \Delta FED_t = constant$			0.00
p − value H_0: Joint Wald of $\gamma \Delta FED_t = 0$			0.00

Table 7

The table reports summary statistics of the time-varying prices of risk for the asset pricing models, conditional on all information variables. The table presents mean, standard deviation, minimum, maximum of the conditional prices as well as the time *t* frequency for which the prices are conditionally significant at 5%. Panel A, B, and C reports the prices of the one-factor CAPM, ICAPM with Bond risk and ICAPM with Macro risk, respectively. The 2711-week sample of test assets covers 361 weeks in the NBER recession periods.

		Panel A	Panel B	Panel C
Conditional Estimates	**IVt**			
Intercept * 100	**Mean**	-0.01	-0.03	0.02
	Std.	0.12	0.10	0.12
	Min	-0.74	-0.73	-0.80
	Max	0.77	0.74	0.67
	% weeks significant	22	15	16
	% recession weeks significant	22	19	19
	% expansion weeks significant	22	15	16
Market	**Mean**	0.61	0.53	0.94
	Std.	2.97	3.35	3.03
	Min	-12.99	-14.59	-12.75
	Max	6.68	7.23	8.00
	% weeks significant	68	68	65
	% weeks POSITIVE & significant	46	44	48
	% recession weeks POSITIVE & significant	23	21	25
	% expansion weeks POSITIVE & significant	49	48	51
Bond	**Mean**		2.99	
	Std.		5.30	
	Min		-8.32	
	Max		23.79	
	% weeks significant		26	
	% recession weeks significant		39	
	% expansion weeks significant		24	
Δ TP	**Mean**			-0.61
	Std.			0.54
	Min			-1.70
	Max			1.96
	% weeks significant			22
	% recession weeks significant			9
	% expansion weeks significant			24
Δ DP	**Mean**			2.59
	Std.			4.07
	Min			-21.26
	Max			13.42
	% weeks significant			44
	% recession weeks significant			46
	% expansion weeks significant			43
Δ FED	**Mean**			0.23
	Std.			0.71
	Min			-3.27
	Max			3.01
	% weeks significant			40
	% recession weeks significant			58
	% expansion weeks significant			37

Table 8

The table reports coefficients for the asset pricing model, ICAPM, with Bond risk or with individual Macro risk. Panel A reports the estimation of uncondi-tional models, assuming constant prices of risk during the sample period. Panel B reports estimation of asset pricing model conditional on all information variables, assuming time-varying prices of risk during the sample period. At the bottom of panel B we report the p-value for the null hypothesis of zero prices of risk as well as the p-value for the null hypothesis of constant prices of risk. P-values are similarly reported for the intercepts. The t-stats are reported in parenthesis and statistical significance levels at 10%, 5%, and 1% are indicated by *,**,*** respectively.

$$R_{i,t} - R_{f,t-1} = \alpha_{t-1} + \lambda_{t-1} Cov_{t-1}(R_{i,t}, R_{m,t}) + \sum_{j=1}^{L} \gamma_{t-1,j}\, Cov_{t-1}(R_{i,t}, z_{j,t}) + \epsilon_{i,t}$$

$$\alpha_{t-1} = \boldsymbol{\alpha}'\, IV_{t-1}$$
$$\lambda_{t-1} = \boldsymbol{\lambda}'\, IV_{t-1}$$
$$\gamma_{t-1,j} = \boldsymbol{\gamma}_j'\, IV_{t-1}$$

Panel A		All bonds		Δ TP		Δ DP		Δ FED	
unconditional	**intercept * 100**	0.02	(0.47)	0.01	(0.28)	0.02	(0.48)	0.02	(0.75)
	Market	0.93***	(3.73)	1.06***	(4.25)	0.78***	(2.82)	1.05***	(4.21)
	Intertemporal Risk	-4.90*	(-1.91)	-0.36	(-1.61)	-1.26**	(-1.97)	0.69***	(4.28)

Panel B									
Conditional Estimates	**IVt**	All bonds		Δ TP		Δ DP		Δ FED	
Intercept * 100	**Constant**	-0.03	(-0.89)	-0.01	(-0.43)	-0.01	(-0.4)	0.01	(0.23)
	xDY	-0.01	(-0.71)	-0.02	(-0.96)	-0.03	(-1.55)	-0.02	(-1.04)
	TP	0.06	(1.6)	0.07*	(1.88)	0.07*	(1.69)	0.07*	(1.69)
	Δ Rf	-0.12	(-1.41)	-0.08	(-1)	-0.07	(-0.87)	-0.12	(-1.43)
	DP	0.08	(0.96)	0.16**	(2.03)	0.16*	(1.9)	0.14*	(1.7)
	realized Vol	-0.01*	(-1.71)	-0.01	(-1.57)	-0.02**	(-2.36)	-0.01	(-1.56)
Market	**Constant**	0.68*	(1.69)	0.57	(1.44)	0.82**	(2.02)	0.39	(0.97)
	xDY	1.42***	(7.89)	1.31***	(7.34)	1.26***	(7.4)	0.97***	(5.58)
	TP	-1.14***	(-2.99)	-1.06***	(-2.74)	-0.66*	(-1.76)	-0.79**	(-2.08)
	Δ Rf	-0.60	(-1.23)	-0.47	(-1.04)	-0.56	(-1.25)	-0.73	(-1.55)
	DP	-2.08***	(-4.45)	-2.23***	(-5.04)	-1.63***	(-3.13)	-1.35***	(-3.12)
	realized Vol	0.07***	(3.17)	0.07***	(2.91)	0.10***	(4.02)	0.06***	(2.82)
Intertemporal Risk	**Constant**	3.71	(1.05)	-0.90***	(-2.59)	2.44*	(1.72)	0.30	(1.26)
	xDY	-3.66***	(-2.72)	0.09	(0.82)	0.24	(0.7)	-0.23***	(-2.96)
	TP	7.68**	(2.17)	-0.33	(-1.29)	2.58**	(2.54)	-0.03	(-0.16)
	Δ Rf	2.69	(0.62)	-0.17	(-0.74)	-2.24*	(-1.73)	-0.20	(-0.89)
	DP	5.92	(1.39)	1.20***	(3.59)	-3.54***	(-3.37)	-1.18***	(-4.06)
	realized Vol	0.01	(0.05)	-0.02	(-0.81)	0.17***	(2.64)	0.04	(1.5)
p − value H_0: Joint Wald of $\alpha_t = constant$		0.11		0.02		0.02		0.04	
p − value H_0: Joint Wald of $\alpha_t = 0$		0.13		0.03		0.03		0.07	
p − value H_0: Joint Wald of $\lambda_t = constant$		0.00		0.00		0.00		0.00	
p − value H_0: Joint Wald of $\lambda_t = 0$		0.00		0.00		0.00		0.00	
p − value H_0: Joint Wald of $\gamma_t = constant$		0.07		0.01		0.00		0.00	
p − value H_0: Joint Wald of $\gamma_t = 0$		0.01		0.01		0.00		0.00	

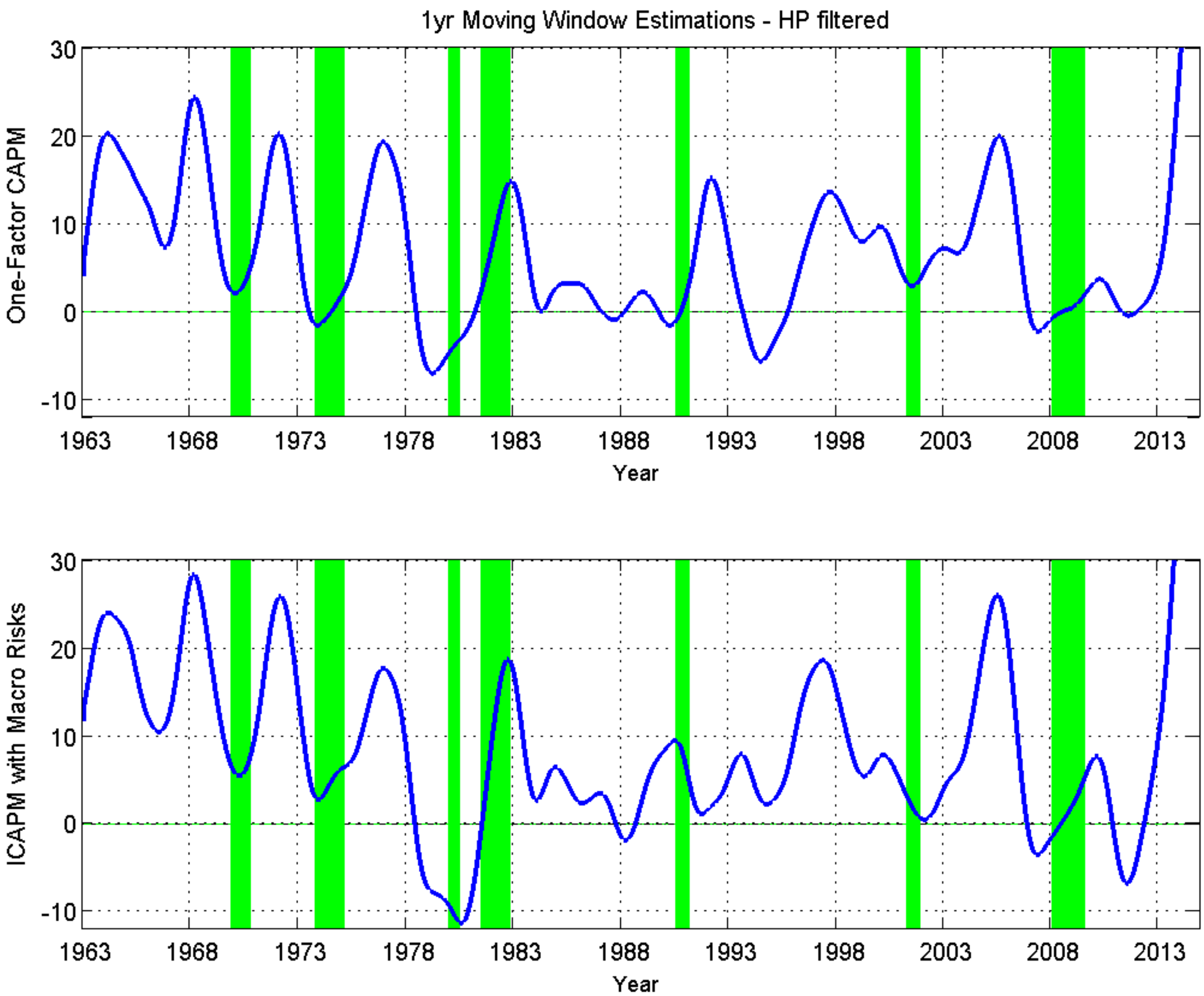

Figure 1: Moving window price of market risk. The top panel plots the price of market risk estimated with a one-year rolling window and constant price one-factor CAPM. The bottom panel plots the price of market risk estimated with a one-year rolling window and constant price ICAMP with macro risk. Green shaded area depicts the NBER recession periods.

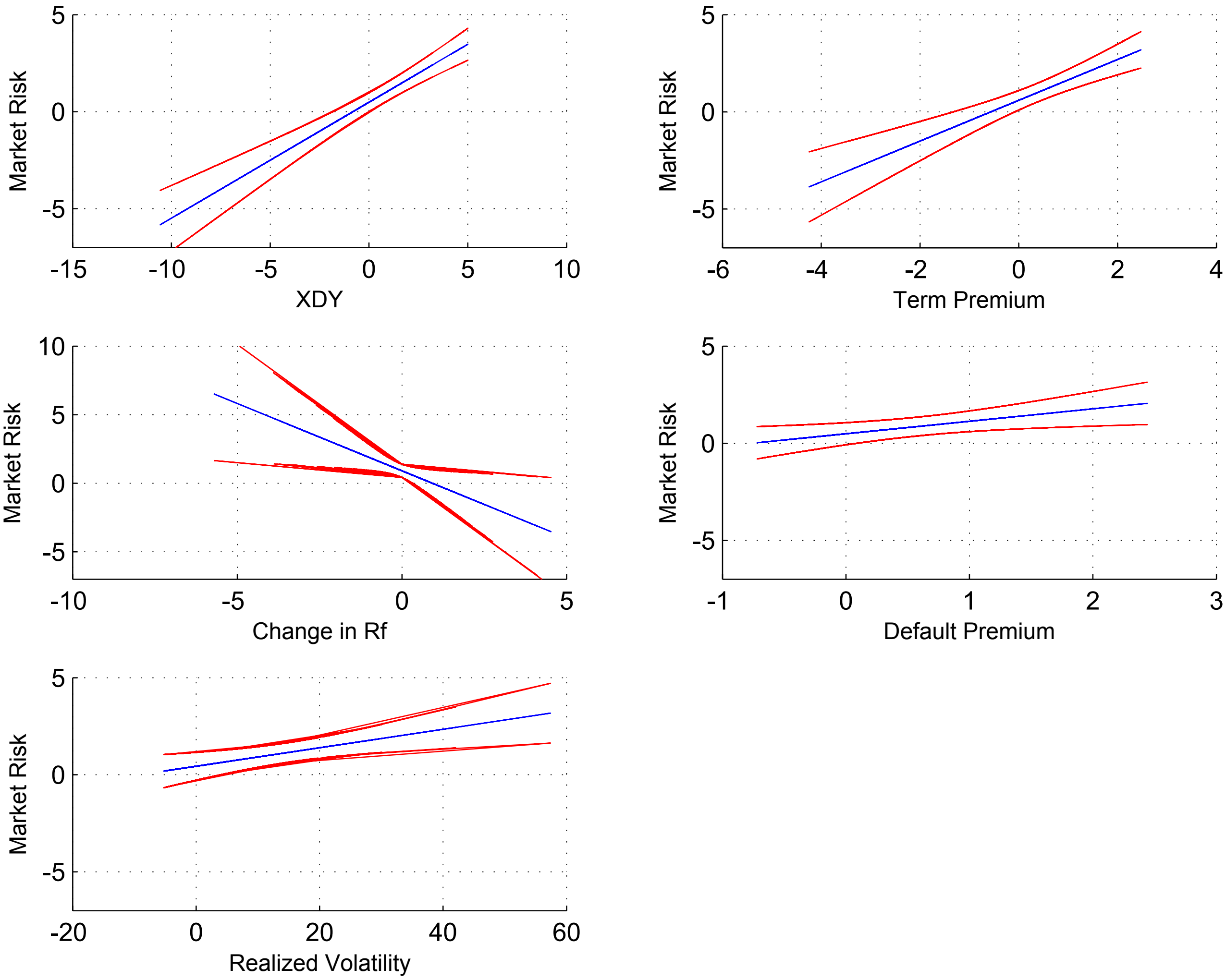

Figure 2: Conditional price of market risk - one IV. The figure plots the price of market risk conditional on one Information variable. Green shaded area depicts values of Information Variables at the NBER recession periods.

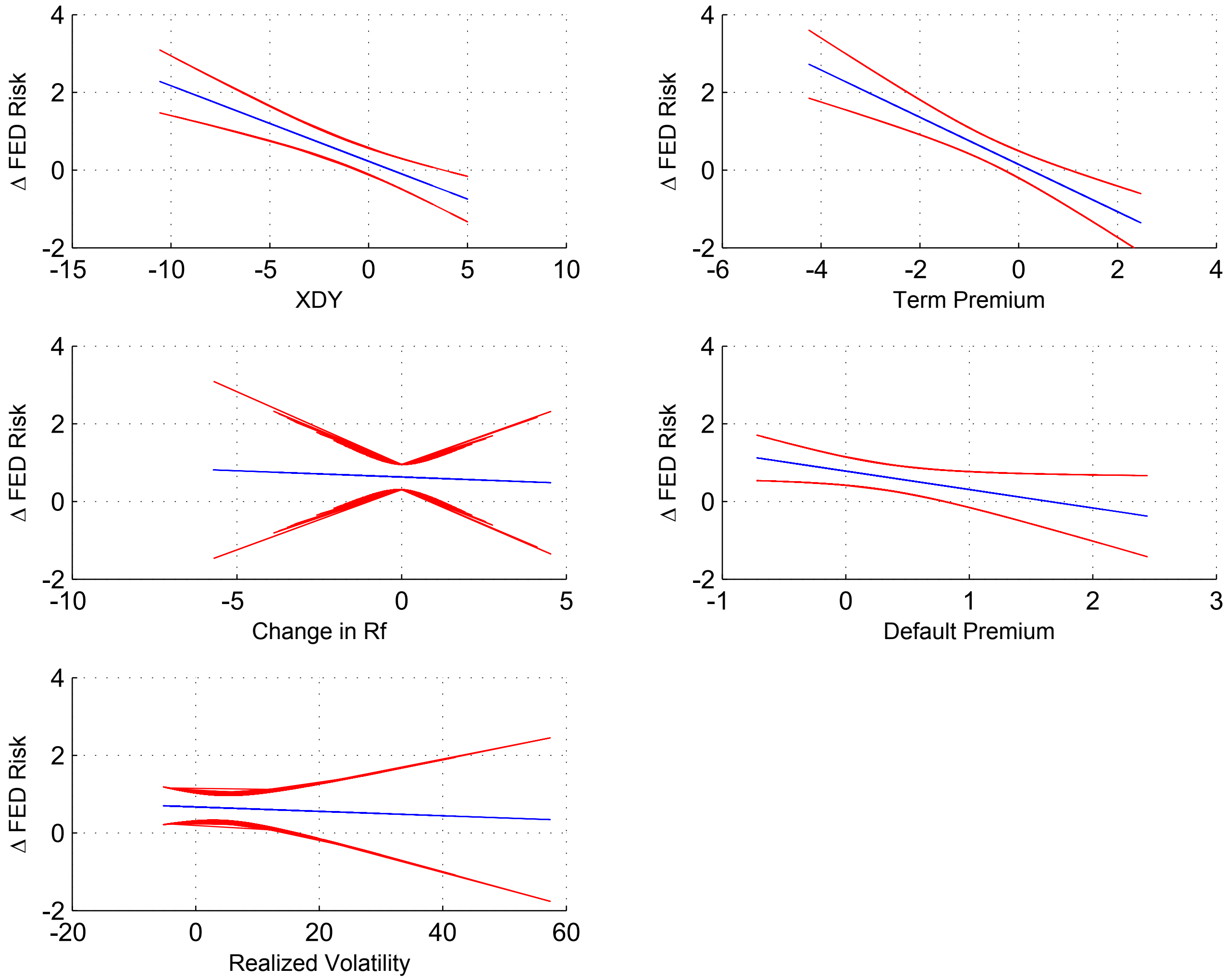

Figure 3: Conditional price of FED risk - one IV. The figure plots the price of FED risk conditional on one Information variable. Green shaded area depicts values of Information Variables at the NBER recession periods.

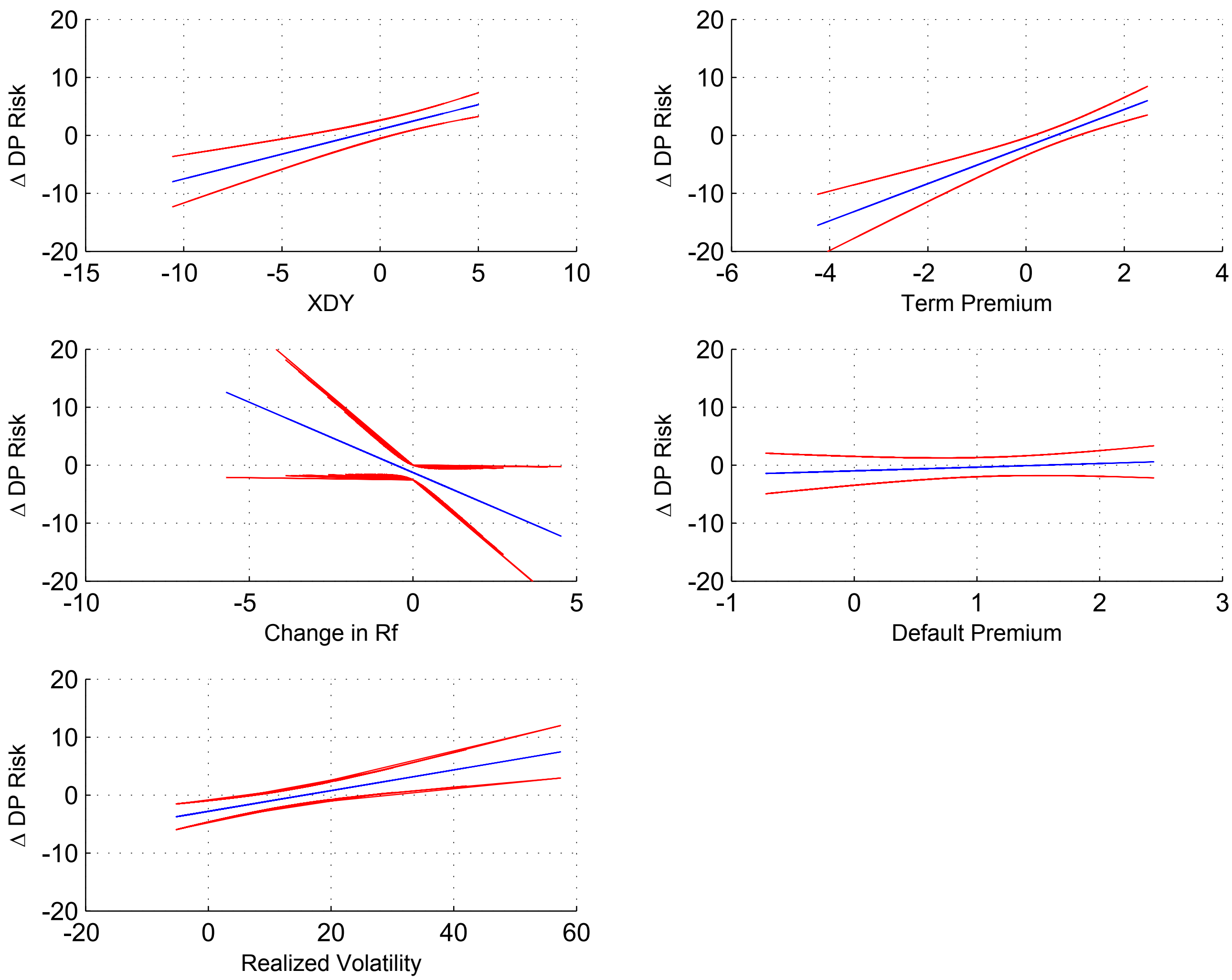

Figure 4: Conditional price of Default Premium risk - one IV. The figure plots the price of default premium risk conditional on one Information variable. Green shaded area depicts values of Information Variables at the NBER recession periods.

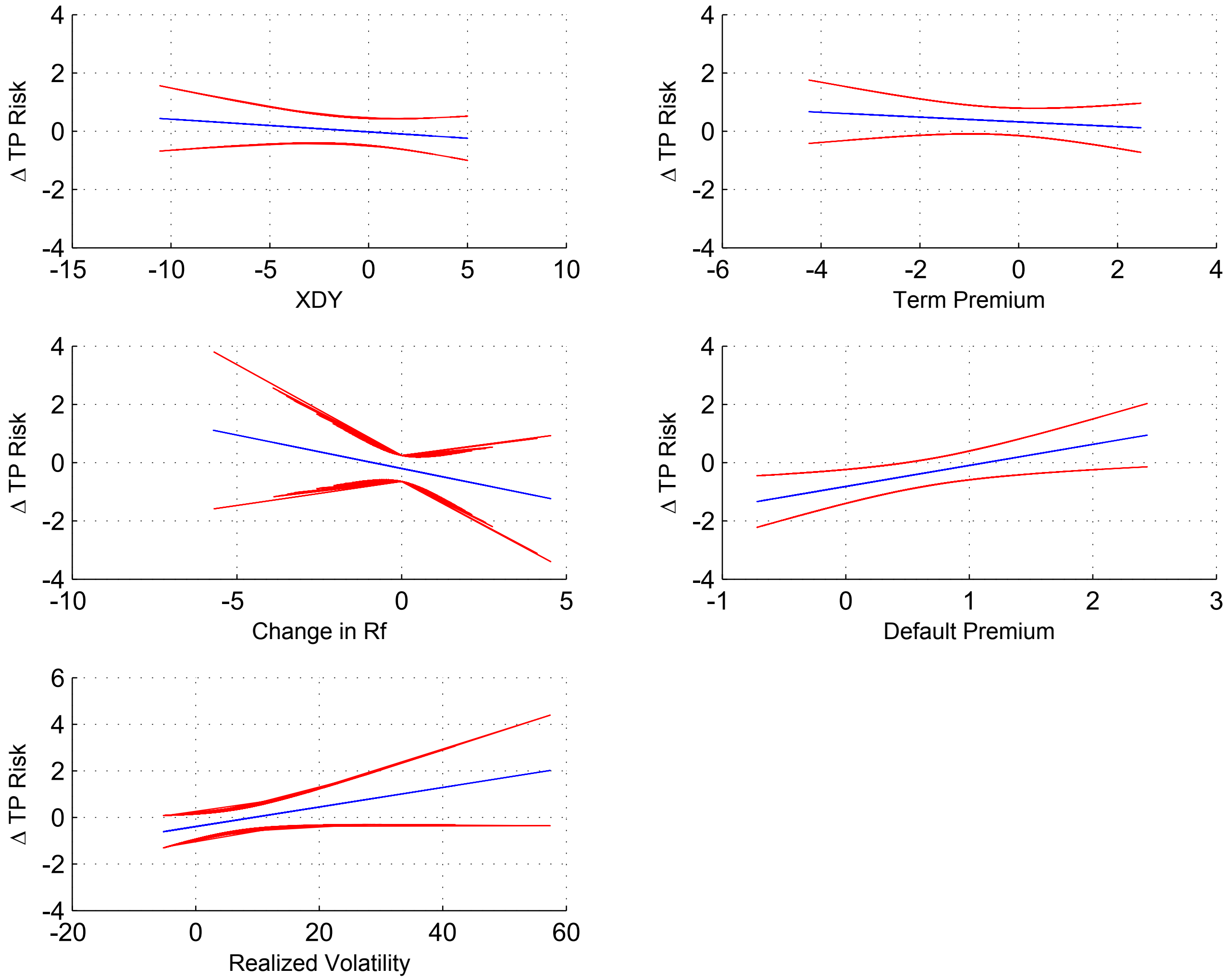

Figure 5: Conditional price of Term Premium risk - one IV. The figure plots the price of Term Premium conditional on one Information variable. Green shaded area depicts values of Information Variables at the NBER recession periods.

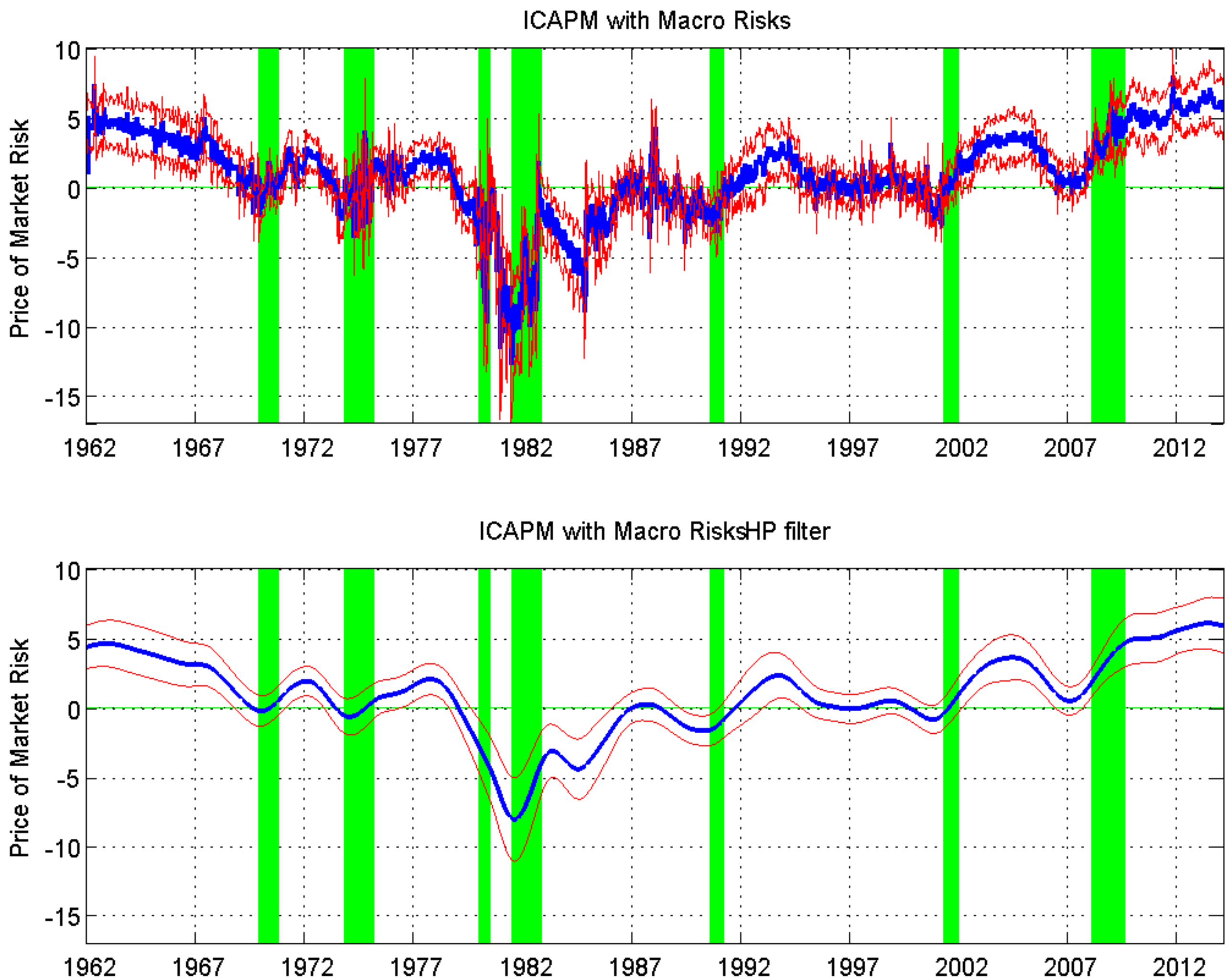

Figure 6-Panel A: Conditional price of market risk - All IV. The top plot shows price of market risk conditional on all information variables estimated from ICAPM with macro risk with its 95% conditional confidence intervals. The bottom plot shows the HP filter of the same price. Green shaded area depicts the NBER recession periods.

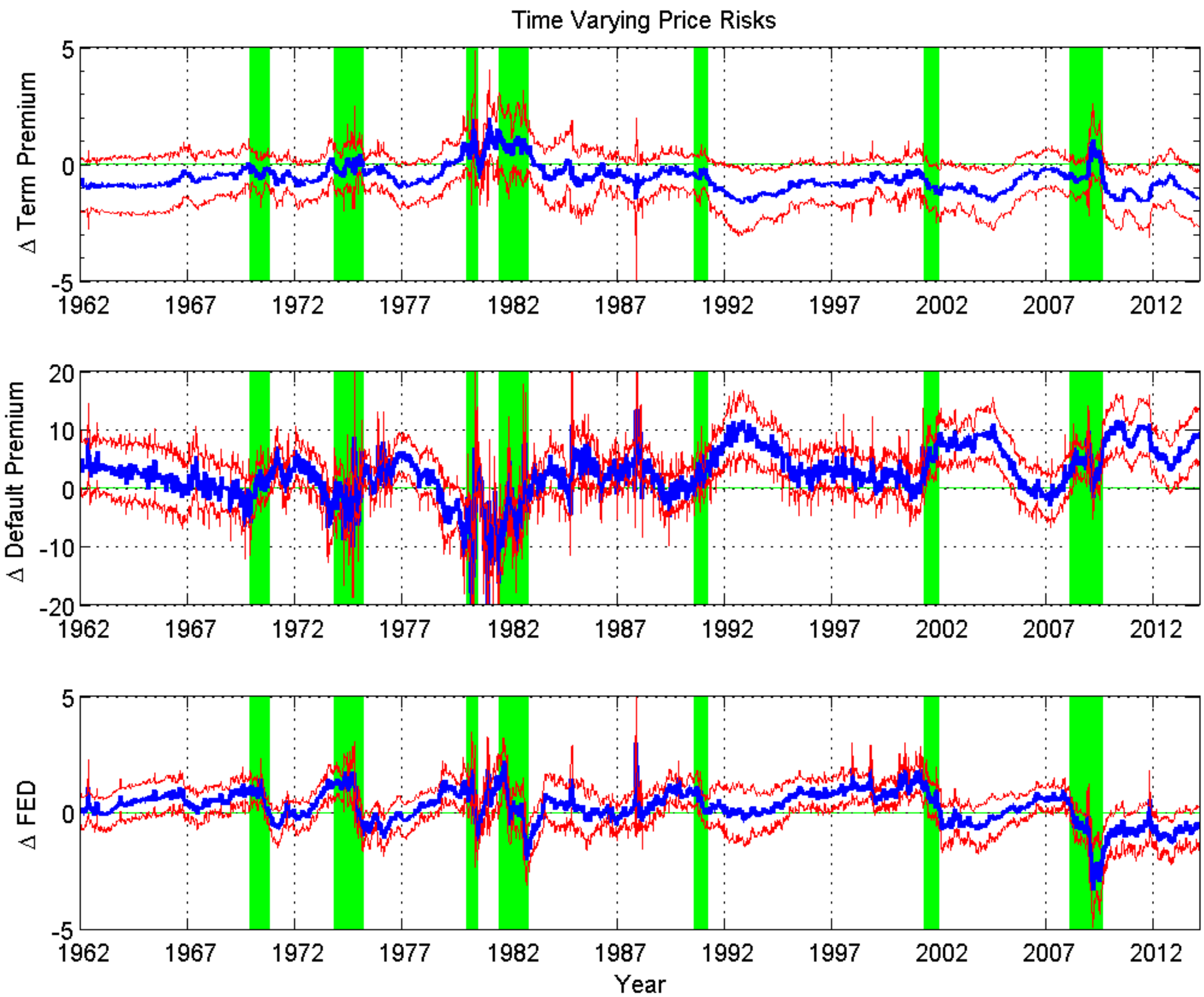

Figure 6-Panel B: Conditional price of Inter-temporal risk - All IV. The top plot shows price of term premium risk, the middle plot shows price of default premium risk and the bottom plot shows price of FED risk. These prices are conditional on all information variables estimated from ICAPM with macro risk. The 95% conditional confidence intervals are shown in red. Green shaded area depicts the NBER recession periods.

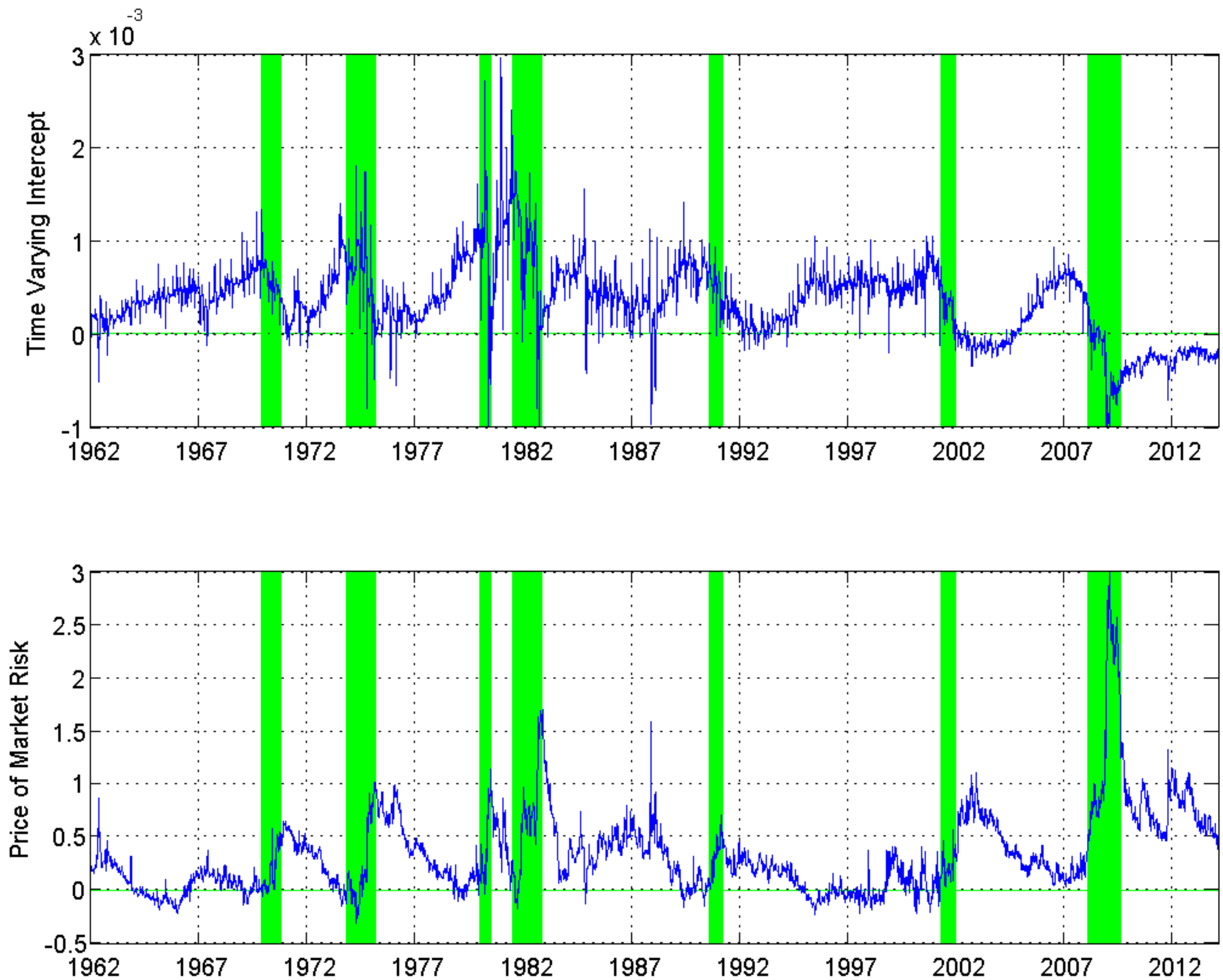

Figure 7: ICAPM with Macro Risk versus one-factor CAPM. The top panel plots the difference between the time-varying intercept estimated from the ICAPM with macro risk and that of the one-factor CAPM. The bottom panel plots the difference between the time-varying price of market risk estimated from the ICAPM with macro risk and that of the one-factor CAPM. Green shaded area depicts the NBER recession periods.

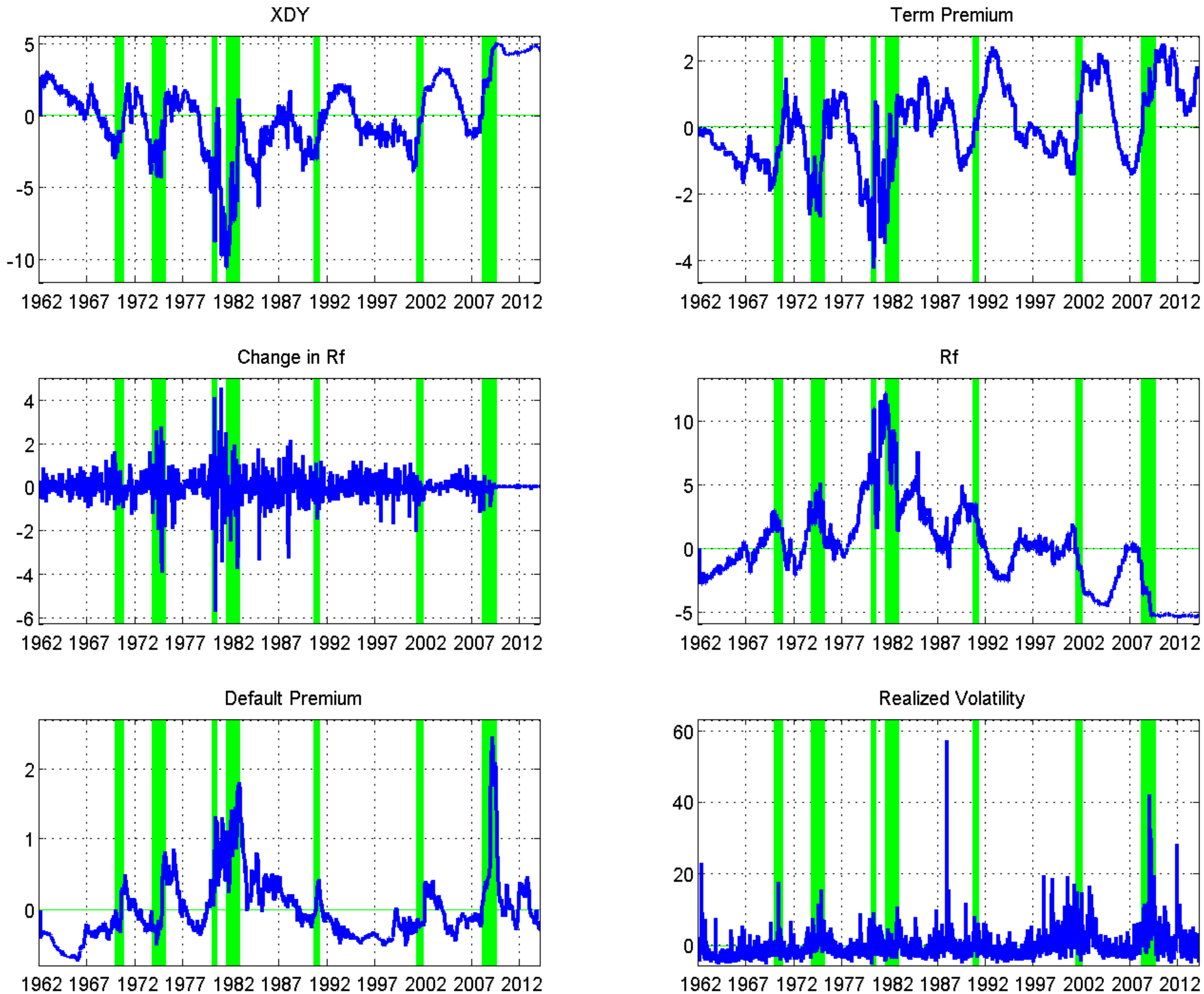

Figure 8: Information Variables. The figure plots the time-series of the excess market dividend yield, term premium, change in risk free rate, level of risk free rate, default premium, and realized market volatility. Green shaded area depicts the NBER recession periods.