Conditional factor models and return predictability *

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Abstract

This paper develops a new approach to examining the time variation of risk premia within the framework of conditional asset pricing models. By combining conditional factor models with approximate present-value relationships we derive a linear relationship between the log stock price and investors' expectations of future factor loadings, risk premia, and cashlows. This framework allows us to estimate conditional risk premia from a cross-sectional regression of log prices on proxies for expected factor loadings and cashflows. We apply this technique to various factor specifications including the CAPM, the three factors advocated by Fama and French (1996), and a five-factor model with economically motivated factors similar to Chen et al. (1986). Consistent with rational pricing we find that, for the majority of the risk factors, the estimated risk premia contain significant information about the future expected returns of the factor portfolios over the sample 1937-2004. Our framework abstracts from the use of ad-hoc conditioning variables, and offers a theoretically appealing approach to modelling the predictable components of stock returns. In recent samples (1978-2004) our estimates of the market risk premium prove to be better forecasters of market returns than the dividend-price ratio and other commonly used forecasting variables. Results from the economic factor model provide evidence that current levels of treasury and corporate bond yields are embedded in the cross section of equity market prices.

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1 Introduction

Over the last thirty years a large number of studies have analyzed whether stock returns vary in a predictable manner. Variables such as the dividend yield, book-to-market ratio and various combinations of interest rates have been identified as key predictors of stock returns. These variables have become popular in the forecasting literature and lend considerable support to the theory that stock returns vary predictably over time.

As evidence for return predictability has grown, so too has interest in whether the observed predictability is consistent with a rational asset pricing model, rather than an indication of inefficient market behavior. Ferson and Harvey (1991) and Ferson and Korajczyk (1995) address this question by examining whether an economic factor model, similar to that proposed by Chen et al. (1986), can explain the return predictability of a diverse set of industry portfolios. They find that, consistent with rational pricing, time variation in factor risk premia explains a large proportion of the predictability of returns. However, more recently Ferson and Harvey (1999) reject that a conditional version of the Fama-French three-factor model captures all the return predictability for twenty five test portfolios. Kirby (1998) and Avramov (2002) also find deviations from conditional, multi-factor asset pricing models.

As is common in the conditional asset pricing literature, these studies use an ad-hoc selection of predictor variables to model the predictable variation of returns. However, this practice leads to concerns over data-mining bias owing to the absence of a well defined theoretical basis for the commonly used predictor variables. Foster et al. (1997) and Ferson et al. (2003) examine the potential extent of data-mining bias and emphasize that tests of conditional factor models are in fact joint tests of both the asset pricing model and the model of investors' conditional expected returns. As highlighted by Kirby (1998), in tests of predictability and multifactor asset pricing models, data-mining bias of predictor variables may overemphasize the level of predictability required to be explained by the asset pricing models, leading to over-rejection of the models. Aside from concerns about data mining, Harvey (2001) shows that estimates of conditional returns can significantly depend on the researcher's choice of lagged predictor variables.

This paper develops a new approach to examining the time variation of risk premia within the framework of conditional asset pricing models. Our approach allows the researcher to estimate conditional returns without recourse to conditioning variables and therefore avoids the aforementioned concerns. The intuition behind our approach is to exploit information about investors' expectations contained in the cross section of market prices. Our starting point is the approximate present value relation developed by Campbell and Shiller (1988), which relates stock prices to investors' conditional expectations of future cashflows and discount rates. Campbell and Shiller (1988) impose structure on this present value relation by specifying a time-series VAR model for investors' conditional expectations. Rather than imposing structure on the time-series dimension, we impose cross-sectional structure on future discount rates and cashflows. Specifically, we assume that a conditional multi-factor model holds, and that future dividend growth rates are a linear function of past growth rates. This leads to a linear relationship between log prices and investors' expectations of future factor loadings, risk premia and cashflows.[1] We extract estimates of conditional risk premia by cross-sectional regressions of stock prices on proxies for future factor loadings and cashflows. This approach of combining present value models with factor pricing models has been applied by Perraudin and Taylor (2002) to derive an analogous relationship for studying the cross-section of corporate bond market prices. Polk et al. (2003) study a similar decomposition of valuation ratios to examine the equity risk premium.

We use our methodology to estimate conditional risk premia for a variety of factor specifications including the CAPM, the three factor model suggested by Fama and French (1996), and the five-factor model with economically motivated factors similar to Chen et al. (1986). Armed with estimates of conditional risk premia we can directly examine the model's implications for return predictability. The central test in our paper focuses on basic asset pricing restriction which relates the factor risk premia, λ_{kt}, to the conditional expected returns of the traded factor portfolios: $E[F_{k,t+1}] = \lambda_{kt}$. This restriction requires that, for each risk factor, variations in the factor risk premium should predict future factor returns. Using time-series regressions we directly test whether the estimated risk premia predict the corresponding factor returns for each risk factor. As previously mentioned, our approach to estimating conditional risk premia avoids the major assumption underpinning previous research in this area: that an ad-hoc predictor variable, or small group of predictor variables, correctly captures investors' conditional expectations. As such our approach provides an alternative way to analyze the ability of conditional factor models to capture return predictability.

[1] We also derive a similar relationship where the cashflow expectations are written in terms of expected ROE growth.

Our results can be interpreted as providing new evidence on the predictability of stock returns. There are two important differences between our tests for predictability and those used previously in the literature. Firstly, our estimates of risk premia (expected returns) come directly from the theoretical restrictions of the asset pricing model and the approximate present value relation. Therefore our estimates of expected returns are theoretically motivated. This contrasts with approaches which require an ad-hoc specification of predictor variables.[2] Secondly, compared to predictability studies which exploit information in the time-series of aggregate portfolios, such as Campbell and Shiller (1988) and Lettau and Ludvigson (2001), our methodology exploits information in the cross section of market prices. Information from the cross section may provide new evidence on return predictability. In particular, Lettau and Ludvigson (2005) argue that positive correlation between dividend growth and expected returns tends to reduce time-series fluctuations in the dividend-price ratio. This renders the dividend-price ratio less able to predict variations in either returns or dividend growth. Our approach, which effectively decomposes the cross section of the dividend-price ratio into conditional expectations of returns and growth, may be better able to uncover predictable variation discount rates.

Our results can be summarized as follows. We use our methodology to estimate conditional risk premia for a variety of multifactor models: the CAPM (Sharpe (1964), Lintner (1965)), the Fama-French three-factor model (Fama and French (1996)), and an economic factor model similar to that proposed by Chen et al. (1986). Our data sample covers the time period 1938-2003. We test the asset pricing relationship linking the factor risk premia to the expected returns on the factor portfolios. In accordance with theory we find that the estimated risk premia predict the corresponding factor returns for the majority of risk factors. These results are particularly strong in recent samples. Our findings provide empirical support for the theoretical relationship between the factor risk premia and the expected returns of the factor portfolios.

Our results provide general evidence on the predictability of aggregate market returns. We find that the estimate of the market risk premium predicts market returns over the full sample (1938-2003). Unlike Polk et al. (2003)[3] we also find strong evidence for predictable

[2]Of course, apart from the CAPM specification, the selection of risk factors is to some extent ad-hoc (see Ferson et al. (1999) for a discussion of the potential pitfalls in identifying risk factors). However, successful asset pricing models have emerged through their ability to price average returns, not for their ability to capture time variation in returns. Therefore we expect data-mining bias to be less of an issue than for predictor variables, which are selected directly on their ability predict returns.

[3]In their working paper Polk et al. (2003) estimate the market risk premium for the CAPM model in a

variations in the market risk premium in recent samples (1978-2004). In fact, the estimated market risk premium proves to be a better forecaster of future market returns than the dividend price ratio, the book-to-market ratio, and several other forecasting variables. It appears that our estimates of the market risk premium capture information about future market returns not provided by predictor variables commonly used in the literature.

The results for the economic factor model offers interesting evidence on the integration of bond and the equity markets. Two of the risk factors in this model are bond-portfolio returns: a treasury factor and a credit factor.[4] The long term expected returns of these portfolios are, to a good approximation, given by the bond yields corresponding to these factor portfolios.[5] This allows us to directly test whether our estimates of the risk premia are equal to the expected returns of the factor portfolio without relying on evidence from predictive regressions as required for the equity factors. We show that the time variation in both treasury and corporate bond yields are indeed captured in the estimated risk premia, that is we find clear evidence that current levels of bond yields are embedded in the cross-sectional distribution of equity prices.

The methodology used to estimate the factor risk premia by cross-sectionally regressing log prices against factor loadings has been developed by Perraudin and Taylor (2004), Perraudin and Taylor (2002), and Taylor (2003) in the corporate bond market. Perraudin and Taylor (2004) use this method to estimate conditional risk premia for bond factor models. Perraudin and Taylor (2002) estimate unconditional risk for the Fama-French risk factors, and Taylor (2003) analyzes the time variation of conditional risk premia for the Fama-French risk factors, and finds evidence that the factor portfolio returns are predicted by the estimated risk premia.

A number of papers in the financial accounting literature share our aim of explaining the cross-section of stock prices (Collins et al. (1997), Dechow et al. (1999)). However,

method similar to ours. They do not consider models other than the CAPM and there are differences in their methodology (for example they map the dependent variable onto an ordinal ranking). They have some success in predicting market returns in the period before 1965. However, they find that their estimates of the market risk premium are not statistically significant at forecasting the market returns over the 1965-2002 period, or over the 1984-2002 period.

[4]The treasury-factor returns are proxied by changes in Moody's Aaa yields, and the credit-factor returns are proxied by the Moody's Baa-Aaa yield spread changes.

[5]The Baa-Aaa yield spread also includes compensation for expected loss due to default. However, for investment grade bonds this component is found to be very small (Elton et al. (2000),Perraudin and Taylor (2002)).

these papers abstract from variations in risk premia as an explanatory variable and focus only on cross-sectional variations in expected cashflows. Exceptions to this include Cornell and Cheng (1995), Gebhardt et al. (2001) and Harris et al. (2003) who estimate expected returns from the Gordon Growth model and then regress these on firm characteristics and market betas. These papers do not share our focus of testing whether the estimated risk premia are consistent with the conditional asset pricing model.

There is a considerable literature examining the estimation of asset pricing models which allow for time-varying expected returns. In particular Jagannathan and Wang (1996), Lettau and Ludvigson (2001) and Ang and Chen (2002) estimate conditional factor models and show that they perform significantly better than the unconditional CAPM.[6] These papers assess whether conditional models better fit the cross-section of average returns rather than directly focusing on their ability to capture time-series predictability as tested in this paper.

The structure of this paper is as follows. Section 2 derives our regression model for estimating conditional risk premia. Section 3 describes the data set. Section 4 presents the results for standard factor models. Section 5 concludes.

2 Combining approximate present-value relationships and conditional factor models

In this section we derive a linear relationship between log prices and future expectations of factor loadings, risk premia and cashflows. We achieve this by combining approximate present value relationships with conditional multi-factor models. Our approach follows Perraudin and Taylor (2002) who derive an analogous relationship for corporate bonds by combining present value relationships with a multi-factor asset pricing model. They derive a relationship between log price (bond yield) and future factor loadings over the remaining life of the bond, risk premia, and expected casfhlows (where the expected cashflows in this case are related to the expected default loss of the corporate bond). We now derive a similar relationship for stocks.

[6] Recent papers examining aspects of conditional factor models include Avramov and Chordia (2002), Wang (2002), and Petkova and Zhang (2003). A paper by Lewellen and Nagel (2003) critically examines whether conditional factor models provide a better explanation of the cross-section of asset returns than unconditional models.

The starting point for our derivation is the loglinear approximate present-value relationship of Campbell and Shiller (1988). This relationship allows for time-variation in both expected returns and dividend growth and provides a convenient framework for examining the cross-sectional determinants of stock prices. The log stock price at the end of period t, p_{it}, is related to the log dividends, d_{it}, in period t and expectations of future dividend growth, $\Delta d_{i,t+j}$, and future returns, $r_{i,t+j}$:

$$p_{it} = \alpha + d_{it} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{i,t+j}) - E_t \sum_{j=1}^{\infty} \rho^{j-1}(r_{i,t+j}) \tag{1}$$

where α and ρ are constants.[7]

At this point Campbell and Shiller (1988) impose a VAR framework on the evolution of expected returns. Instead, we impose cross-sectional structure on the discount rates and the expected cashflows to derive a cross-sectional regression equation. First we shall discuss the parameterisation of the discount rates, followed by the cashflow terms.

The key step in our derivation is to substitute the discount rate terms in the last term in equation (1) by a conditional factor model expression for expected returns, ($E_t[R_{i,t+j}] = E_t[\sum_{k=1}^{N} \beta_{ik,t+j-1}\lambda_{k,t+j-1}]$).[8] This leads to

$$p_{it} = \alpha + d_{it} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{i,t+j}) - \sum_{j=0}^{\infty} \rho^{j} \left(\sum_{k=1}^{N} E_t[\beta_{i,k,t+j}\lambda_{k,t+j}] \right) \tag{2}$$

To make the equation empirically tractable we assume that the risk premia follow a mean reverting AR(1) process, $\lambda_t = a + q\lambda_{t-1} + \epsilon_t$, and that the risk exposures are constant over time, $\beta_{ikt} = \beta_{ik}$. These assumptions lead to the following expression for the cross-sectional distribution of prices:

$$p_{it} = \alpha + d_{it} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{i,t+j}) - \sum_{k=1}^{N} \beta_{ik}\lambda'_{kt} \tag{3}$$

where $\lambda'_{kt} = k_1 + k_2\lambda_{kt}$, and the constants k_1 and k_2 are given by $k_1 = \frac{a}{1-q}(\frac{1}{1-\rho} - \frac{1}{1-\rho q})$ and

[7] The parameters α and ρ are related to the average log dividend yield: $\rho \equiv \frac{1}{1+exp(<d_t-p_t>)}$, and $\alpha \equiv -ln(\rho)/(1-\rho) - ln(1/\rho - 1)$. Following Campbell and Vuolteenaho (2004) we set ρ equal to 0.95 throughout the paper.

[8] With j=1 this equation gives the standard expression for expected returns for a conditional k-factor model: $E_t[R_{i,t+1}] = \sum_{k=1}^{N} \beta_{ik,t}\lambda_{k,t}$.

$k_2 = \frac{1}{1-\rho q}$. For simplicity we set a=0, q=1[9] which results in the following:

$$p_{it} = \alpha + d_{it} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{i,t+j}) - \frac{1}{1-\rho} \sum_{k=1}^{N} \beta_{ik}\lambda_{kt} \quad (4)$$

Equation (4) suggests that the risk premia can be estimated by cross-sectional regression of prices on dividends, proxies for dividend growth and risk exposures.

To complete the model we also need to specify the cross-section structure of cashflow expectations. Without a simple, implementable model explaining the cross-section of dividend growth we proxy this term by the past dividend growth of the firm over the last M years (we set M=1 in our basline specification). This results in a cross-sectional regression specification:

$$p_{it} = \alpha + \theta d_{it} + \eta_t g_{i,t-M\to t-1} - \frac{1}{1-\rho} \sum_{k=1}^{N} \lambda_{kt}\beta_{ik} \qquad \text{for all assets } i, \quad (5)$$

where λ_{kt}, α, η_t and θ_t are the parameters to be estimated.[10] We will refer to the above formulation (equation (5)) as the D/P formulation. We note that this specification uses information available at time t to estimate investors' conditional expectations of risk premia.

The assumption that the factor loadings are constant (see Ferson and Gibbons (1985) and Ferson and Keim (1993) previous analysis of this type of model) is important because it allows us to abstract from cross-correlation terms between betas and risk premia. Whether cross terms are important for describing the cross section of average returns is currently an open question (Lewellen and Nagel (2003)). The standard approach to modelling such terms is to allow the betas to be driven by an ad-hoc set of conditioning variables, however this is the kind of modelling assumption which this paper wishes to avoid making. Therefore, in our baseline empirical implementation the beta sensitivities β_{ik} are calculated by simple time-series regressions using the past five years of data.

We also consider an alternative specification of our model where the expected cashflow terms are rewritten in terms of book values and the return on equity (ROE) rather than in terms of dividends and dividend growth. This transformation of variables is analogous

[9]However, this assumption is not essential. The parameters a and q can be inferred from fitting an AR(1) process to the estimates of λ'. This would result in altering our estimates of risk premia by a constant linear transformation which has no affect on the predictability results. Since this relies on the time series of λ conforming to an AR(1) process we prefer to present the unadulterated estimates.

[10]Theory suggests that $\theta = 1$, however for robustness we do not impose this constraint.

to the rewriting of the standard Gordon Growth model in terms of earnings and book variables by Ohlson (1995). The starting point is the approximate present value relation of Vuolteenaho (2002):

$$p_{it} = \alpha + b_{it} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(e_{i,t+j}) - E_t \sum_{j=1}^{\infty} \rho^{j-1}(r_{i,t+j}) \tag{6}$$

where b_{it} is the log book equity per share at the end of period t, and e_{it} is the ROE over period t for asset i.[11] Once again we combine this approximate present value relationship with a conditional factor model to impose cross-sectional structure on the model. Making the same assumptions as above for the discount rates and proxying the ROE terms by the past ROE of the firm we obtain the following cross-sectional regression specification:

$$p_{it} = \alpha + \theta b_{it} + \eta_t e_{i,t-M\to t-1} - \frac{1}{1-\rho} \sum_{k=1}^{N} \lambda_{kt}\beta_{ik} \qquad \text{for all assets } i, \tag{7}$$

where λ_{kt}, α, η_t and θ_t are the parameters to be estimated by cross-sectional regression. We will refer to the above formulation (equation (7)) as the B/M formulation. Although we implement both approaches, this B/M formulation has several potential empirical advantages. Firstly, since we estimate our models on the cross-section of individual stocks, the number of stocks eligible for estimating equation (5) is limited to those stocks with non-zero dividends. In contrast the B/M formulation requires information on earnings and book values for which there is a larger cross section of stocks, particularly in the recent subsample after the rapid expansion of the numbers of stocks in COMPUSTAT. Secondly, as discussed by Vuolteenaho (2002), the modelling of the dividend decision for individual firms is potentially more complicated than the modelling of their earnings.

3 Data

3.1 Test assets and book equity values

The equity data used in this paper includes firms in the intersection of the CRSP database of NYSE, AMEX, and NASDAQ listed stocks, and the COMPUSTAT database. Market capitalization is taken from the CRSP database and is defined as the price multiplied by the number of shares outstanding. Book equity values are assumed to become known

[11]Return on equity is defined as follows $e_t = log(1 + E_t/B_{t-1})$ where E_t is the earnings over period t, and B_{t-1} is the book value at the end of period t-1.

six months after the end of the fiscal year. The book equity is given by COMPUSTAT data item 60. Assuming that the clean surplus condition holds, earnings are calculated as the change in book equity plus CRSP dividends. Book equity values prior to the start of the COMPUSTAT database are obtained from the Fama-French historical book equity database.[12] Our dataset covers the period from 1926-2004.

3.2 Construction of risk factor returns

Value weighted excess returns on the market are calculated from the return on all NYSE, AMEX, and NASDAQ stocks minus the one-month treasury bill rate. The Fama-French model specifies the following three factors: the market portfolio, the SMB portfolio (consisting of a long position in small firms and a short position in large firms), the HML portfolio (consisting of a long position in high book-to-market firms and a short position in low book-to-market firms). The construction of the Fama-French factors is described in Fama and French (1996).

The economic factor model uses five macroeconomic factors to proxy for economic risks influencing security returns. We use factors similar to those proposed in previous studies such as Chen et al. (1986), Ferson and Harvey (1991) and Chan et al. (1998). The five factors are: the market return, the monthly growth rate of industrial production (IP), a default free treasury return calculated from changes in the Moody's Seasoned Aaa Corporate Bond Yield (TREAS)[13], the change in the difference between the Moody's Seasoned Aaa and Baa Corporate Bond Yields (DEF), the unanticipated inflation factor (INF) calculated as in Ferson and Harvey (1991).[14] Our paper focuses on testing the theoretical relationship linking the factor expected returns and the factor risk premia. This relationship only holds when the factors are traded portfolios, therefore, for the non-traded factors IP and INF, we construct equity portfolio returns that mimic the exposures of these economic factors. We use a technique by Chan et al. (1998) based on the portfolio formation approach of Fama and French (1993a). At yearly portfolio formation dates the stocks are ranked on their loadings for a particular factor. The mimicking portfolio return for this factor is defined as

[12]This data is available from the website of K. French at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[13]For consistency with the DEF factor we use the Aaa bond yield as a proxy for the default free yield. The results are the same if we use a long term treasury bond yield.

[14]An IMA(1,1) model is fitted to the inflation rate and the error term is used as the unanticipated inflation shock.

the difference between the value weighted return of the top quintile and the bottom quintile of stocks. In this way monthly mimicking returns are calculated.

4 Empirical implementation and results

4.1 Cross-sectional regression results and forecasting regressions

In this section we estimate conditional risk premia for the CAPM, the Fama-French three-factor model, and an economic five-factor model using the general methodology outlined in section (2). Our main focus is to test whether the estimated risk premia predict the returns of the factor portfolios in accordance with the basic asset pricing restriction:

$$E_t[F_{k,t+1}] = \lambda_{kt} \tag{8}$$

where $F_{k,t+1}$ denotes the portfolio factor return for the k^{th} risk factor.

The factor models we consider vary in both number and specification of risk factors. The CAPM provides theoretical justification for employing a single equity market index. Fama and French (Fama and French (1989a), Fama and French (1993b)) specify three factors: a market index, a size factor (SMB), and a book-to-market factor (HML). Economic factor models describe the risk exposure with a set of risk factors related to macroeconomic variables. We choose a parsimonious model with the following risk factors: the market return, an industrial production factor (IP), a treasury term structure factor (TREAS), a credit factor (DEF), and an unanticipated inflation factor (INF). The construction of these factors is described in Section 3.

The question of which test assets to use is somewhat difficult. Most studies implement asset pricing models on large portfolios constructed by sorting securities on a criterion of interest. Common practice is to test models on the twenty five Fama-French equity portfolios formed from sorting on size and book-to-market. Roll (1977) argues that forming portfolios can potentially impair asset pricing tests by reducing cross-sectional variation in some characteristics of the test assets. This consideration is particularly relevant to our study. A wide variation in risk exposure across the test assets is required to obtain accurate estimates of the risk premia. This rules out using the twenty five Fama-French portfolios which exhibit little variation in market betas. In fact, standard Fama-MacBeth cross-sectional regressions lead to risk premia on both the market and SMB portfolios which are statistically insignificant over the 1965-1998 period (Lettau and Ludvigson (2001)). A natural choice is to perform cross-sectional regressions on individual assets. This approach is taken by Brennan et al. (1998) for similar reasons. The cost of this approach is that it increases the error in variables (EIV) bias owing to the larger measurement error in the factor loadings (Black et al. (1972)). For the purpose of this study it is preferable to trade off potential bias against the benefits of a wider variation in beta sensitivities, therefore, our tests are performed on the cross-section of individual stocks.[15]

Table 1 reports the results from implementing the cross-sectional regression models (equations (5, 7)). This table contains the average of the monthly cross-sectional regression estimates over our sample period of 193706-200406.[16] Panel A reports estimates from D/P formulation of the model (equation 5), and Panel B reports estimates from the B/M formulation (equation 7). Each row corresponds to a different factor model: the CAPM, the Fama-French three-factor model (FF), and the economic model (ECON). Columns 3-9 contain the risk premia estimates expressed in terms of percent per annum and below each estimate are standard errors, in parentheses, adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)). Columns 10-11 report the regression coefficients on cashflow variables.

Examining the estimates of the risk premia we find that with the exception of the market price of risk, the risk premia are either positive or are statistically insignificant in both model specifications. However, the results for the market price of risk suggest mis-specification in either the asset pricing component of the model or the cashflow component of the model. Given the existing asset pricing literature we have good reason to believe that our model will be mis-specified to some extent. For example, it is well known that the CAPM does not fully describe the average returns of assets particularly in recent samples (see for example Fama and French (1996)). Lettau and Ludvigson (2001) report the results from estimating the Fama-French three-factor model on the Fama-French test assets over the time period 1965-2001. They find that the risk premia on both the market and SMB portfolios are small and statistically insignificant. They also test a variety of other asset pricing models and frequently estimate a negative market risk premium. Ferson and Harvey (1991) implement an economic factor model similar to the one used in this paper. They

[15]In results not reported we find that aggregating assets into portfolios reduces the information contained in the risk premia estimates, and weakens their ability to predict future factor returns.

[16]We require 5 years of data from which to calculate the equity mimicking portfolios in addition to the five years of data to calculate the factor loadings, therefore our test sample starts in 193706.

find, in post 1980 data, that their point estimates of the market risk premium are often negative. Our approach is to assume that, owing to the inevitable mis-specification of the model, our estimates of the market risk premium are likely to be biased. The focus of our paper is to test whether fluctuations in the risk premia, after controlling for bias, contain important information about future factor returns.

Examining the casfhlow terms (columns 10-11, Table 1) we find that the estimates of θ are close, but systematically lower than the theoretical value of unity. The estimates of the dividend growth term η_t are negative for the D/P formulation. This suggests that the past dividend growth for an individual firm is negatively related to the expected future dividend growth.[17] The estimates of the ROE term η_t are positive, suggesting that firms with high past ROE have high expected future ROE.

We now investigate whether the risk premia contain information about future factor returns. We test the theoretical requirement $E_t[F_{k,t+1}] = \lambda_{kt}$ by regressing the factor returns ($F_{k,t+1}$) against the estimated risk premia (λ_{kt}). The predictive regressions take the form $F_{k,t+1} = \alpha + \beta\lambda_{kt} + \epsilon_{t+1}$. However, inspection of our estimated risk premia reveals that, although most of the series are stationary, some contain a constant trend over the sample. For example Figure 2 shows the estimates of the market risk premium for the CAPM for both the D/P and B/M formulations. In order to focus on the relatively short term fluctuations of the risk premia we detrend the data before performing the predictive regressions.[18] Tables 2 and 3 report results for risk premia estimated from the D/P formulation of our model (equation 5). Each panel in the table corresponds to a different factor model (CAPM,FF,ECON). The rows in each panel report the one-year-ahead forecasts of the factor return using the corresponding factor risk premia as the explanatory variable. Results are reported for the full sample and three subsamples. Since our cross-section regressions are estimated on individual stock data we might expect our estimates to be influenced by large changes in the number of stocks in the sample. Figure 1 illustrates the variation in the numbers of stocks over our sample period. We see that the cross section of matched CRSP-COMPUSTAT stocks varies substantially over time particularly as a result of the large expansion in COMPUSTAT'S database in the seventies. We choose our subsamples to avoid major breaks in the numbers of stocks which are likely to affect our tests

[17]As a robustness check we also perform regressions where the expected future dividend growth rate is proxied by the ex-post dividend growth rate, rather than the past dividend growth rate. In accordance with theory the estimates of η are positive.

[18]Specifically we perform predictive regressions on the transformed risk premiums: $\lambda_t \to \lambda_t - t*(\lambda_N - \lambda_0)/N$

of the conditional factor models. Our subsamples are 193706-196805, 196806-197805, and 197805-200405.

Each row reports the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. In general the interpretation of predictive regressions is complicated by the effects of small sample bias, as studied by Nelson and Kim (1993) and Stambaugh (1999), and the effects of using overlapping observations in small samples (Valkanov (2003)). Our study avoids the latter concern because we consider non-overlapping returns. To assess whether our results are sensitive to small sample bias we perform Monte Carlo simulations of the predictability regression under the null hypothesis of no predictability. From the distribution of the betas under the null hypothesis we can generate critical values which account for finite sample bias.[19] Since our model implies a positive beta coefficient in the predictive regression we test the null hypothesis that beta is zero against the alternative that it is greater than zero. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of the estimated betas, generated under the null hypothesis of no predictability.

Examining the forecasting results for the full sample in Table 2 we find that for the CAPM model the estimated market risk premium strongly predicts the future market returns. The forecasting power of the risk premium is statistically significant at the 1% level. The $\bar{R}^2$ of 21% is substantial for predictive regressions at yearly horizons. The results for the market risk premium hold for all three factor models with similar levels of significance.

The Fama-French model contains the risk factors SMB and HML. According to the asset pricing restriction (equation 8) the fluctuations in these risk premia should predict factor returns. However, our results indicate that these risk premia do not strongly forecast factor returns over the full sample.

Turning to the economic factor model we find that in addition to the market risk premium the inflation risk premium strongly predicts the corresponding inflation-factor returns, and the industrial production factor is significant at the 5% level. The risk premia associ-

[19]Specifically we analyze the following data generating process considered by Stambaugh (1999): $F_{t+1} = \alpha + u_{t+1}$, $\lambda_{t+1} = \gamma + \rho\lambda_t + \epsilon_{t+1}$. The parameters in the data-generating process are set to sample estimates. We generate 10,000 artificial samples under the null hypothesis of no predictability. For each sample we run the predictive regression: $F_{t+1} = \alpha + \beta\lambda_t + \mu_{t+1}$ and from the distribution of the beta estimates we can estimate the relevant fractiles.

ated with the bond market factors TREAS and DEF do not appear to contain information about future bond returns. However, for the bond market factors there is an alternative way to test whether the risk premia are correctly capturing the time variation in expected bond returns. For these factors the risk premia are, to a good approximation, known a priori from the corresponding bond yields. For example the expected excess return of the Baa bond in excess of the Aaa bond over the maturity of the bond is closely approximated by the Baa-Aaa yield spread.[20] Similarly, for the TREAS factor the bond yield associated with this factor (the Aaa bond yield) is equivalent to the expected return over the life of the bond. Figure 3 shows the estimated risk premium for the TREAS factor and the corresponding long term Aaa bond yield. Both series are demeaned and normalized to unit standard deviation, but are not detrended. It can be seen that the fluctuations in the premium estimated from equity data is strongly correlated with the variation in bond market yield (the correlation in the changes is equal to 0.55). Figure 4 focuses on the recent subsample where the correspondence between the Aaa bond yield and the estimated risk premia is even clearer. Figure 5 shows a similar result for the DEF risk premia and the long term credit yield spread (ie Baa-Aaa yield spread). Again the estimated risk premia tracks the long term expected return on the bond (the correlation in the changes is equal to 0.40). These results provide evidence that current levels of treasury and corporate bonds yields are embedded in the cross section of equity market prices in a way which is consistent with the predictions of a multi-factor asset pricing model.

Next we analyze the predictive regression results in the subsamples for the D/P formulation (equation 5). As mentioned, our tests of the asset pricing restriction could be affected by discontinuous changes in the cross section of stocks over time so it is instructive to examine samples over which there are no large variations in cross section. Also it is important to see if the predictability results are robust to changes in sample. Table 2 reports the results for the recent subsample (1978-2004). The results for this sample are largely consistent with those for the full sample. However, in the recent sample the HML risk premia predicts returns of the HML factor at the 5%. This result is perhaps not surprising given that the importance of the Fama-French factors for explaining deviations from CAPM only becomes significant in post 1965 samples. Table 3 reports the results for the small subsample (1968-1978) and the earlier sample (1938-1968). The results for the early sample (1937-1968) show that only the market risk premium is a significant predictor

[20] The Baa-Aaa yield spread also includes compensation for expected loss due to default. However, for investment grade bonds this component is found to be very small (Elton et al. (2000),Perraudin and Taylor (2002)).

variable in this period.

It is apparent that the forecasting results for market returns do not appear to be affected by the negative estimate of the market risk premium. It is reasonable to suppose that the estimates of the market risk premium, $\hat{\lambda}_t$, are biased by an amount c, which varies slowly over time i.e. $\hat{\lambda}_t = \lambda_t - c$. This type of bias would allow us to detect the time variation of the market return inherent in λ_t. Our predictability results support such an interpretation.

Tables 4 and 5 report the asset pricing tests for risk premia estimated from the B/M formulation (equation 7). This formulation uses book and earnings data to model the expected cashflow component of the model. Figure 1 shows that the number of stocks in the cross section is below that for the D/P formulation in early samples but rises significantly in the latter sample and significantly exceeds the stocks in the D/P sample. Table 4 reports the tests of the asset pricing restriction for the full model. The results are broadly consistent with the D/P formulation however the significance levels tend to be lower. The market risk premium predicts the market returns at the 5% level for two of the asset pricing models. The results for the Fama-French model indicate that neither the SMB or HML risk premia are significant predictors over the full sample. The results for the economic factor model show that risk premia associated with the market, the inflation factor and the default factor have ability to predict future factor returns. Contrary to the asset pricing model the results for the TREAS factor indicate that for one-year-ahead forecasts the risk premia is negatively related to future returns. However, by comparing bond risk premia with the corresponding bond yields we confirm the results previously obtained for the D/P formulation i.e. that the risk premia track the long-term expected return of the bonds. These results are qualitatively similar to those illustrated in Figures 3-5 however, to conserve space we do not report them. The correlations between the estimated risk premia and corresponding bond yields are similar to those reported for the D/P formulation (0.53 and 0.34 are the correlations in the changes for the TREAS and DEF factors respectively).

Results for the recent sample (1978-2004) are shown in Table 4. The forecasting power is strong for the market risk premium for the economic factor model specification. Also the HML risk premium and the credit factor risk premium are significant at the 5% level. Results for the early sample reported in Table 5 show no evidence of predictability by the factor risk premia.

In summary, our results provide evidence consistent with the theoretical prediction linking the risk premia to expected factor returns for the majority of risk factors considered. The most robust evidence is for the market risk premium which predicts market returns for the majority of the samples and asset pricing models. For the HML factor the evidence is strongest in the recent samples. For the bond factors the strongest evidence comes from the comparison of the risk premia estimates with long term bond yields. The only risk factor for which we have no evidence consistent with the asset pricing relationship is the SMB factor.

4.2 Comparison with alternative forecasting variables

The methodology in this paper provides a theoretically motivated approach to modelling return predictability. A natural question is whether the risk premia capture information not contained in standard predictor variables commonly used in the literature. The aggregate log dividend-price ratio and the log book-to-market ratio are well known examples of predictor variables (Campbell and Shiller (1988), Fama and French (1988)). We define the dividend-price ratio as the total dividends paid over the prior year divided by the current level of the NYSE-AMEX-NASDAQ value weighted index. The book-to-market ratio is calculated as the total book value divided by the sum of the capitalization of those stocks with non-missing book equity. Book equity values are assumed to become known six months after the end of the fiscal year. Fama and French (1989b) find that the term spread (Moody's seasoned Aaa bond yield minus the one-year Treasury bond yield) and the default spread (DEF) (the difference between the Baa and Aaa corporate bond yields) predict market returns over their test samples.

Table 6 presents the forecasting regressions for yearly excess market returns over the full sample (193706-200405) and Table 7 presents the results over the recent sub-sample (197806-200405). The estimates of the market risk premium λ are taken from the D/P formulation (equation 5). The table reports coefficient estimates from OLS regression of aggregate market returns on lagged predictor variables. Each row lists the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), adjusted R^2 values, and confidence intervals at the 5% and 1% levels calculated by Monte Carlo simulation. Confidence intervals are one-sided for our estimate of the market risk premium regression, and two-sided for the other predictor variables (we quote the closest critical value to the beta estimate).

Over the full sample the forecasting power of the log dividend-price ratio[21] and the log book-to-market ratio predict returns with roughly similar statistical significance using Newey-West t-statistics but are insignificant using Stambaugh's correction.[22] The TERM and DEF variables do not appear to have much significance over our sample. The final two regressions compare the predictive power of the market risk premium and the dividend-price ratio and the bond yields using multivariate regressions. The market premium's forecasting power is not affected by addition of the log dividend-price ratio which is insignificant in the multivariate regression. The final regression shows that the market premium has significant marginal explanatory power over the TREAS and DEF predictor variables.

In the recent sub-sample (Table 7) our estimate of the market risk premium dominates the other predictor variables. In particular, it has much higher levels of statistical significance than both the dividend-price ratio and the book-to-market ratio.

Overall our results show that estimates of the market risk premium generated from the cross-section of market prices contains significant additional information about future market returns not contained in standard predictor variables commonly used in the literature.

5 Alternative specifications

We have considered various other specifications of the model to check the robustness of our results. In particular we have estimated risk premia for alternative specifications of the cashflow component of the model. For the D/P formulation (equation 5) and the B/M formation (equation 7) we obtain qualitatively the same results with past growth of dividends and ROE calculated from the previous five years rather than the one year horizon used in the baseline regressions. We have also implemented a model where the dividend growth for each asset i is assumed to follow an AR(1) process: $g_{it} = a_i + q g_{i,t-1} + \epsilon_{it}$. Under this model the expected cashflow growth term in equation 5 becomes:

$$E_t \sum_{j=1}^{\infty} \rho^{j-1}(g_{i,t+j}) = \frac{a_i}{(1-q_i)(1-\rho)} - \frac{a_i q_i}{(1-q_i)(1-\rho q_i)} + \frac{q_i g_{it}}{(1-\rho q_i)} \tag{9}$$

[21] Our results are similar to those obtained by Lettau and Ludvigson (2005). Taking approximately the same sample as theirs (1948-2001) we obtain similar estimates for the forecasting power of the dividend/price ratio (Our estimates are Beta=12.1, t-stat=1.88, $\hat{R}^2$=0.075, noting that returns are expressed in percent).

[22] We note that the persistence of the dividend-price ratio and the book-to-market ratio is much higher than for our detrended estimates of the market risk premia. An AR(1) process fitted to yearly data gives coefficients of 0.92,0.93,0.63 for the dividend-price ratio, book-to-market ratio, and risk premium respectively.

At each point in time and for each asset, this term is calculated using the parameters estimated from the past five years of quarterly dividend data. The results from this model are qualitatively similar to our baseline results, as are the results from the corresponding approach to modelling the ROE.

6 Conclusion

Using a technique similar to that previously used in the corporate bond market (Perraudin and Taylor (2004), Perraudin and Taylor (2002), Taylor (2003)) risk premia are estimated by cross-sectionally regressing log prices on the securities' factor loadings while controlling for expected future cashflows. We test the asset pricing relationship linking the factor risk premia to the expected returns on traded factor portfolios for the CAPM, Fama-French three-factor model, and an economically motivated five-factor model. In accordance with theory, we find evidence that the estimated risk premia contain information about future expected factor returns.

Our focus on testing the condition $E_t[F_{k,t+1}] = \lambda_{kt}$ differs from the standard asset pricing tests found in the literature which generally focus on testing whether the intercept term in the standard regression is statistically different from zero. We believe that consideration of our alternative test will lead to further improvements in the ability of factor models to rationally explain the predictable time variation in asset returns.

This paper presents a theoretically motivated way to model the predictability of asset returns. Given the current concerns over data mining for predictor variables (Foster et al. (1997), Ferson et al. (2003)), our methodology offers an attractive alternative to the standard approach to modelling predictability.

Table 1: **Average estimates of risk premia**

This table reports the average cross-sectional regression coefficients over the full sample 193706-200409 for the D/P formulation (equation 5) and the B/M formation (equation 7) of the model. Each row corresponds to a different asset pricing model: the CAPM, Fama-French three-factor model (FF), and an economically motivated factor model (ECON). The risk premia estimates are denoted as follows: market premium (market), size risk premium (SMB), book-to-market risk premium (HML), Industrial Production (IP), Treasury premium (TREAS), Credit risk premium (DEF), inflation risk premium (INF). The risk premia estimates are expressed in terms of percent per annum. The cashflow variables are as follows: the coefficient of the log dividend term (θ), and the coefficient of the dividend growth term (η). Standard errors are in parenthesis and are adjusted for serial correlation in the residuals using the Newey-West correction Newey and West (1987).

		Risk Premia							*Cashflow terms*		
	Const	Market	SMB	HML	IP	TERM	DEF	INF	θ	η	$< R^2 >$
					Panel A: D/P formulation (equation 5)						
CAPM	-3.11	-1.98	-	-	-	-	-	-	0.93	-0.17	0.89
	(0.06)	(0.21)	-	-	-	-	-	-	(0.01)	(0.02)	(0.00)
FF	-3.21	-2.09	0.12	1.22	-	-	-	-	0.90	-0.19	0.90
	(0.06)	(0.19)	(0.11)	(0.15)	-	-	-	-	(0.01)	(0.02)	(0.00)
ECON	-3.15	-2.14	-	-	0.72	0.05	0.05	0.46	0.91	-0.19	0.89
	(0.07)	(0.19)	-	-	(0.12)	(0.03)	(0.02)	(0.13)	(0.01)	(0.02)	(0.00)
					Panel B: B/M formulation (equation 7)						
CAPM	-0.60	0.47	-	-	-	-	-	-	0.92	0.71	0.78
	(0.08)	(0.29)	-	-	-	-	-	-	(0.01)	(0.09)	(0.01)
FF	-0.75	-0.33	0.82	1.50	-	-	-	-	0.89	0.57	0.81
	(0.07)	(0.18)	(0.14)	(0.11)	-	-	-	-	(0.02)	(0.08)	(0.01)
ECON	-0.66	-0.22	-	-	1.33	-0.04	0.18	0.72	0.90	0.61	0.81
	(0.06)	(0.19)	-	-	(0.27)	(0.04)	(0.04)	(0.20)	(0.01)	(0.08)	(0.01)

Table 2: **Testing risk premia estimated from the D/P formulation**

This table presents results from testing the asset pricing restriction $E_t[R_{k,t+1}] = \lambda_{kt}$ for each risk factor k, where λ_{kt} is the risk premia estimate from the the D/P formulation (equation 5). The predictive regressions take the form $R_{k,t+1} = \alpha + \beta\lambda_{kt} + \epsilon_{t+1}$ and are estimated on non-overlapping data. Each row reports the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of betas generated under the null hypothesis of no predictability. Each panel corresponds to a different factor model: CAPM, Fama-French three-factor model, and an economically motivated factor model. Risk factors are denoted as follows: market premium (M), size risk premium (SMB), book-to-market risk premium (HML), industrial production (IP), treasury premium (TREAS), credit risk premium (DEF), inflation risk premium (INF).

Full sample: 193706-200406, Yearly returns

	β	S.E.(β)	T-stat	R^2	5%	1%
Panel A: CAPM						
R_M	10.03	2.15	4.67	0.21	5.15	7.60
Panel B: Fama-French 3-factor model						
R_M	9.49	2.98	3.18	0.14	5.56	7.89
R_{SMB}	-0.45	2.28	-0.20	-0.01	4.31	6.29
R_{HML}	3.81	2.86	1.33	0.04	5.37	7.69
Panel C: Economic factor model						
R_M	8.31	2.31	3.59	0.12	5.57	7.95
R_{IP}	3.34	2.10	1.59	0.06	3.30	4.70
R_{TREAS}	-9.11	6.13	-1.49	0.05	8.80	12.17
R_{DEF}	-1.12	3.10	-0.36	-0.01	4.88	7.15
R_{INF}	6.11	1.36	4.48	0.15	4.23	6.02

Recent sub-sample: 197806-200406, Yearly returns

	β	S.E.(β)	T-stat	R^2	5++	1++
Panel A: CAPM						
R_M	15.42	4.26	3.62	0.31	10.92	15.26
Panel B: Fama-French 3-factor model						
R_M	17.85	5.07	3.52	0.37	11.75	16.72
R_{SMB}	2.74	2.39	1.15	-0.01	7.32	10.70
R_{HML}	12.98	5.21	2.49	0.18	12.20	17.81
Panel C: Economic factor model						
R_M	14.14	4.57	3.10	0.27	11.62	17.14
R_{IP}	3.81	2.11	1.80	0.03	7.17	10.02
R_{TREAS}	-10.49	9.14	-1.15	0.03	15.18	21.48
R_{DEF}	3.39	3.05	1.11	0.00	6.23	8.75
R_{INF}	3.46	1.90	1.82	0.04	8.39	12.38

Table 3: **Testing risk premia estimated from the D/P formulation**

This table presents results from testing the asset pricing restriction $E_t[R_{k,t+1}] = \lambda_{kt}$ for each risk factor k, where λ_{kt} is the risk premia estimate from the D/P formulation (equation 5). The predictive regressions take the form $R_{k,t+1} = \alpha + \beta\lambda_{kt} + \epsilon_{t+1}$ and are estimated on non-overlapping data. Each row reports the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of betas generated under the null hypothesis of no predictability. Each panel corresponds to a different factor model: CAPM, Fama-French three-factor model, and an economically motivated factor model. Risk factors are denoted as follows: market premium (M), size risk premium (SMB), book-to-market risk premium (HML), industrial production (IP), treasury premium (TREAS), credit risk premium (DEF), inflation risk premium (INF).

Sub-sample: 196806-197806, Yearly returns

	β	S.E.(β)	T-stat	R^2	5%	1%
Panel A: CAPM						
R_M	0.44	4.57	0.10	-0.12	14.61	20.87
Panel B: Fama-French 3-factor model						
R_M	0.05	3.51	0.01	-0.12	13.74	19.56
R_{SMB}	5.55	4.09	1.36	-0.06	35.28	49.68
R_{HML}	12.93	5.27	2.45	0.08	22.08	32.47
Panel C: Economic factor model						
R_M	0.47	3.45	0.14	-0.12	16.11	23.58
R_{IP}	-0.24	4.47	-0.05	-0.12	14.14	21.58
R_{TREAS}	0.56	11.77	0.05	-0.12	38.67	55.43
R_{DEF}	-8.99	6.61	-1.36	-0.01	20.54	36.98
R_{INF}	13.56	3.55	3.82	0.37	20.33	31.36

Sub-sample: 193706-196806, Yearly returns

	β	S.E.(β)	T-stat	R^2	5++	1++
Panel A: CAPM						
R_M	14.04	2.77	5.06	0.28	9.99	14.30
Panel B: Fama-French 3-factor model						
R_M	9.98	2.18	4.57	0.14	9.27	13.33
R_{SMB}	-5.43	2.90	-1.88	0.12	3.30	6.22
R_{HML}	0.78	3.71	0.21	-0.03	8.92	12.51
Panel C: Economic factor model						
R_M	8.92	2.26	3.94	0.10	10.56	15.84
R_{IP}	5.00	2.06	2.43	0.14	5.86	8.55
R_{TREAS}	0.38	5.92	0.06	-0.03	9.49	12.94
R_{DEF}	-6.64	10.75	-0.62	0.00	11.74	16.84
R_{INF}	6.83	2.04	3.35	0.14	7.80	10.91

Table 4: **Testing risk premia estimated from the B/M formulation**

This table presents results from testing the asset pricing restriction $E_t[R_{k,t+1}] = \lambda_{kt}$ for each risk factor k, where λ_{kt} is the risk premia estimate from the B/M formulation (equation 7). The predictive regressions take the form $R_{k,t+1} = \alpha + \beta\lambda_{kt} + \epsilon_{t+1}$ and are estimated on non-overlapping data. Each row reports the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of betas generated under the null hypothesis of no predictability. Each panel corresponds to a different factor model: CAPM, Fama-French three-factor model, and an economically motivated factor model. Risk factors are denoted as follows: market premium (M), size risk premium (SMB), book-to-market risk premium (HML), industrial production (IP), treasury premium (TREAS), credit risk premium (DEF), inflation risk premium (INF).

Full sample: 193706-200406, Yearly returns

	β	S.E.(β)	T-stat	R^2	5%	1%
Panel A: CAPM						
R_M	4.74	1.74	2.73	0.10	3.91	5.67
Panel B: Fama-French 3-factor model						
R_M	3.36	2.18	1.54	0.02	4.69	6.64
R_{SMB}	-0.07	1.79	-0.04	-0.02	4.30	6.01
R_{HML}	4.84	4.49	1.08	0.03	5.96	8.30
Panel C: Economic factor model						
R_M	4.58	2.02	2.27	0.06	4.58	6.54
R_{IP}	-0.24	0.57	-0.42	-0.01	2.03	2.93
R_{TREAS}	-8.96	3.71	-2.42	0.08	7.68	10.86
R_{DEF}	0.27	1.77	0.15	-0.01	2.86	4.08
R_{INF}	4.22	1.03	4.09	0.10	3.48	4.96

Recent sub-sample: 197806-200406, Yearly returns

	β	S.E.(β)	T-stat	R^2	5++	1++
Panel A: CAPM						
R_M	10.99	5.56	1.98	0.18	9.73	13.43
Panel B: Fama-French 3-factor model						
R_M	10.94	7.14	1.53	0.13	12.61	17.96
R_{SMB}	0.20	3.16	0.06	-0.04	8.87	12.42
R_{HML}	17.47	4.07	4.29	0.28	12.80	17.89
Panel C: Economic factor model						
R_M	16.11	5.80	2.78	0.28	11.52	16.04
R_{IP}	1.94	1.93	1.01	-0.02	9.83	14.13
R_{TREAS}	-16.35	7.57	-2.16	0.12	17.49	24.04
R_{DEF}	10.98	3.77	2.91	0.23	9.29	13.42
R_{INF}	6.73	2.81	2.40	0.09	10.71	15.09

Table 5: **Testing risk premia estimated from the B/M formulation**

This table presents results from testing the asset pricing restriction $E_t[R_{k,t+1}] = \lambda_{kt}$ for each risk factor k, where λ_{kt} is the risk premia estimate from the B/M formulation (equation 7). The predictive regressions take the form $R_{k,t+1} = \alpha + \beta\lambda_{kt} + \epsilon_{t+1}$ and are estimated on non-overlapping data. Each row reports the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of betas generated under the null hypothesis of no predictability. Each panel corresponds to a different factor model: CAPM, Fama-French three-factor model, and an economically motivated factor model. Risk factors are denoted as follows: market premium (M), size risk premium (SMB), book-to-market risk premium (HML), industrial production (IP), treasury premium (TREAS), credit risk premium (DEF), inflation risk premium (INF).

Sub-sample: 196806-197806, Yearly returns

	β	S.E.(β)	T-stat	R^2	5%	1%
Panel A: CAPM						
R_M	6.67	8.76	0.76	-0.03	16.42	22.70
Panel B: Fama-French 3-factor model						
R_M	2.67	6.19	0.43	-0.10	15.28	21.70
R_{SMB}	3.91	3.62	1.08	-0.09	27.11	36.96
R_{HML}	26.82	7.33	3.66	0.35	26.90	41.01
Panel C: Economic factor model						
R_M	5.31	6.66	0.80	-0.05	17.62	23.97
R_{IP}	-8.97	8.27	-1.08	0.00	24.30	37.48
R_{TREAS}	5.65	9.74	0.58	-0.09	35.22	51.08
R_{DEF}	-22.12	15.13	-1.46	0.05	43.81	69.33
R_{INF}	24.33	4.02	6.05	0.61	30.06	44.51

Sub-sample: 193706-196806, Yearly returns

	β	S.E.(β)	T-stat	R^2	5++	1++
Panel A: CAPM						
R_M	3.24	2.06	1.57	0.03	6.31	9.09
Panel B: Fama-French 3-factor model						
R_M	2.10	2.21	0.95	-0.01	7.28	10.77
R_{SMB}	-1.97	3.34	-0.59	-0.01	5.84	8.15
R_{HML}	-2.36	3.85	-0.61	-0.02	7.62	11.05
Panel C: Economic factor model						
R_M	2.58	2.19	1.18	0.00	6.84	9.64
R_{IP}	0.24	0.76	0.32	-0.03	2.63	3.98
R_{TREAS}	-1.34	3.09	-0.43	-0.03	6.37	9.23
R_{DEF}	-0.55	3.17	-0.17	-0.03	3.85	5.43
R_{INF}	3.71	1.48	2.50	0.08	4.29	6.46

Table 6: **Forecasting market returns: a comparison with other predictor variables**

This table compares the forecasting ability of commonly used predictor variables with our estimate of the market risk premium, λ, estimated from the D/P formulation (equation 5). Regressions use non-overlapping yearly returns over the full sample (193706-200405). The table reports coefficient estimates from OLS regression of aggregate market returns on lagged predictor variables. Each row lists the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of betas generated under the null hypothesis of no predictability. Tests are one sided for the regression using our estimate of the market risk premium, and two-sided for the other predictor variables (for the two sided tests the beta fractile closest to the estimated beta is quoted, and this may be negative).

Full sample: 193706-200406, Yearly returns

	β	S.E.(β)	T-stat	R^2	5%	1%
λ	10.03	2.15	4.67	0.21	5.15	7.60
d-p	13.89	5.84	2.38	0.09	22.05	29.17
b-m	13.42	6.53	2.06	0.07	26.80	-7.90
TERM	2.53	1.51	1.68	0.01	3.78	4.94
DEF	-2.78	3.30	-0.84	-0.01	-8.62	-11.46
λ	9.25	2.87	3.22	0.21	-	-
d-p	2.80	6.38	0.44	0.00	-	-
λ	10.53	1.93	5.44	0.26	-	-
TERM	4.05	1.37	2.96	0.00	-	-
DEF	-3.57	4.15	-0.86	0.00	-	-

Table 7: **Forecasting market returns: a comparison with other predictor variables over the recent sample**

This table compares the forecasting ability of commonly used predictor variables with our estimate of the market risk premium, λ, estimated from the D/P formulation (equation 5). Regressions use non-overlapping yearly returns over the recent sample period (197806-200405). The table reports coefficient estimates from OLS regression of aggregate market returns on lagged predictor variables. Each row lists the OLS estimate of the regression coefficient, t-statistics adjusted for generalized serial correlation in the residuals using the Newey-West correction (Newey and West (1987)), and adjusted R^2 values. Under the headings 5% and 1% we report the beta values corresponding to the relevant fractile of the distribution of the estimated betas, generated under the null hypothesis of no predictability. Tests are one sided for the regression using our estimate of the market risk premium, and two-sided for the other predictor variables (for the two sided tests the beta fractile closest to the estimated beta is quoted, and this may be negative).

Recent sample: 197806-200405, Yearly returns

	β	S.E.(β)	T-stat	R^2	5%	1%
λ	15.42	4.26	3.62	0.31	10.92	15.26
d-p	3.68	7.58	0.49	-0.03	-7.38	-13.51
b-m	3.35	8.68	0.39	-0.03	-8.04	-13.11
TERM	3.37	1.60	2.11	0.04	5.05	6.84
DEF	-2.26	7.44	-0.30	-0.04	-15.23	-22.10
λ	15.30	4.12	3.71	0.29	-	-
d-p	1.82	6.63	0.27	0.00	-	-
λ	14.69	4.66	3.16	0.28	-	-
TERM	1.75	1.48	1.18	0.00	-	-
DEF	1.99	7.28	0.27	0.00	-	-

Figure 1: Time variation of number of stocks sample

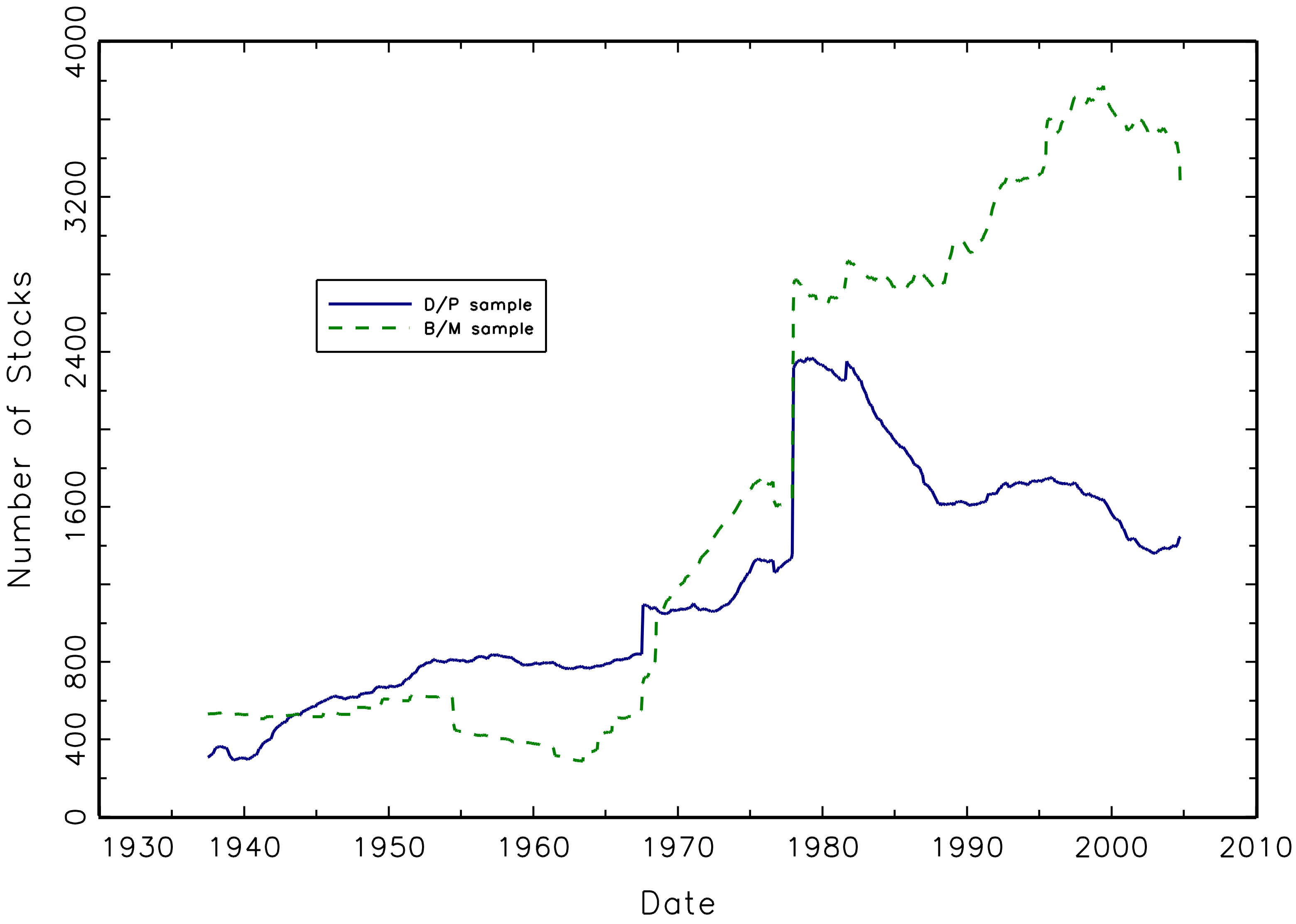


Figure 2: Estimates of market risk premium

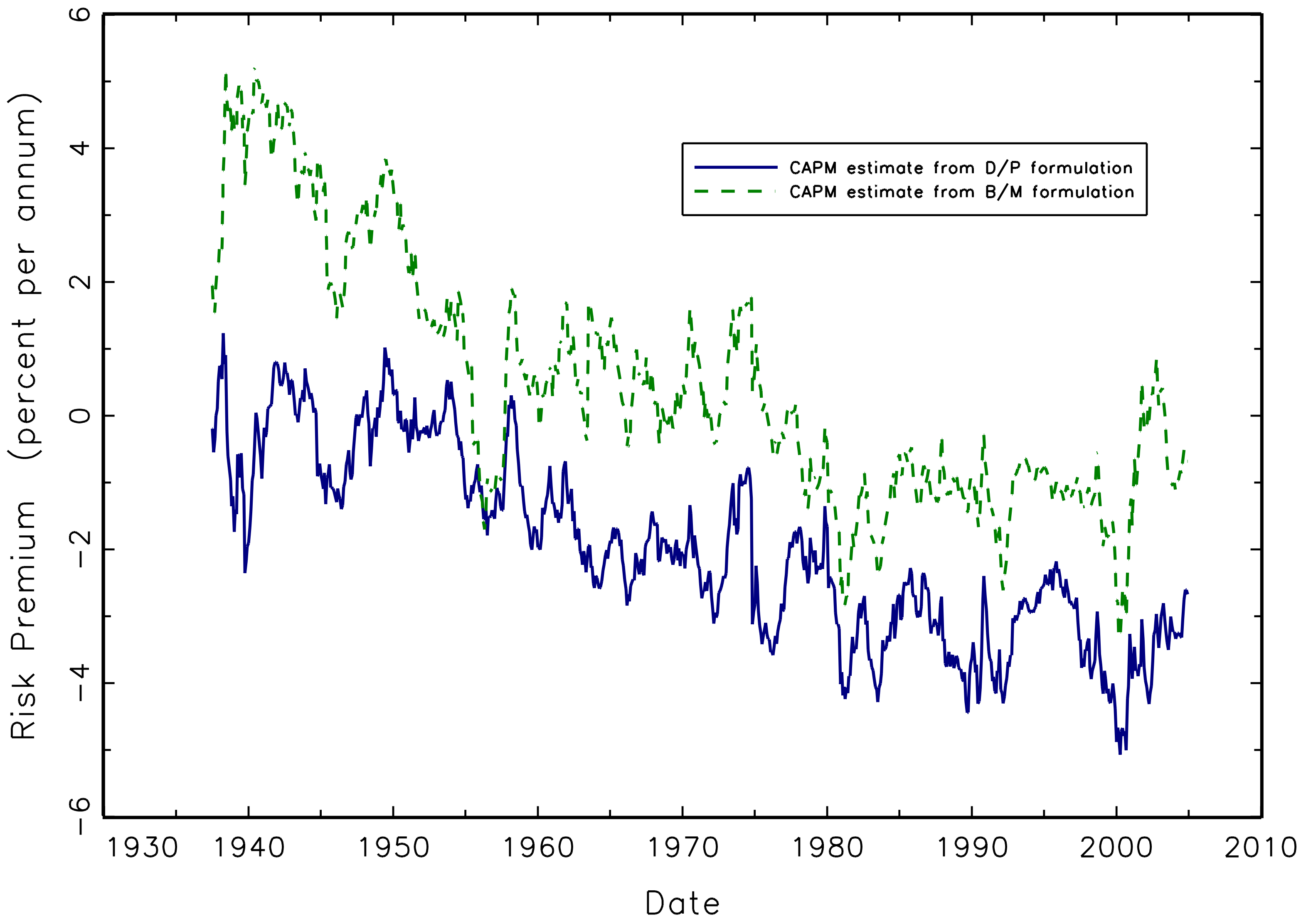


Figure 3: Comparison of the estimated treasury risk premium and the AAA bond yield

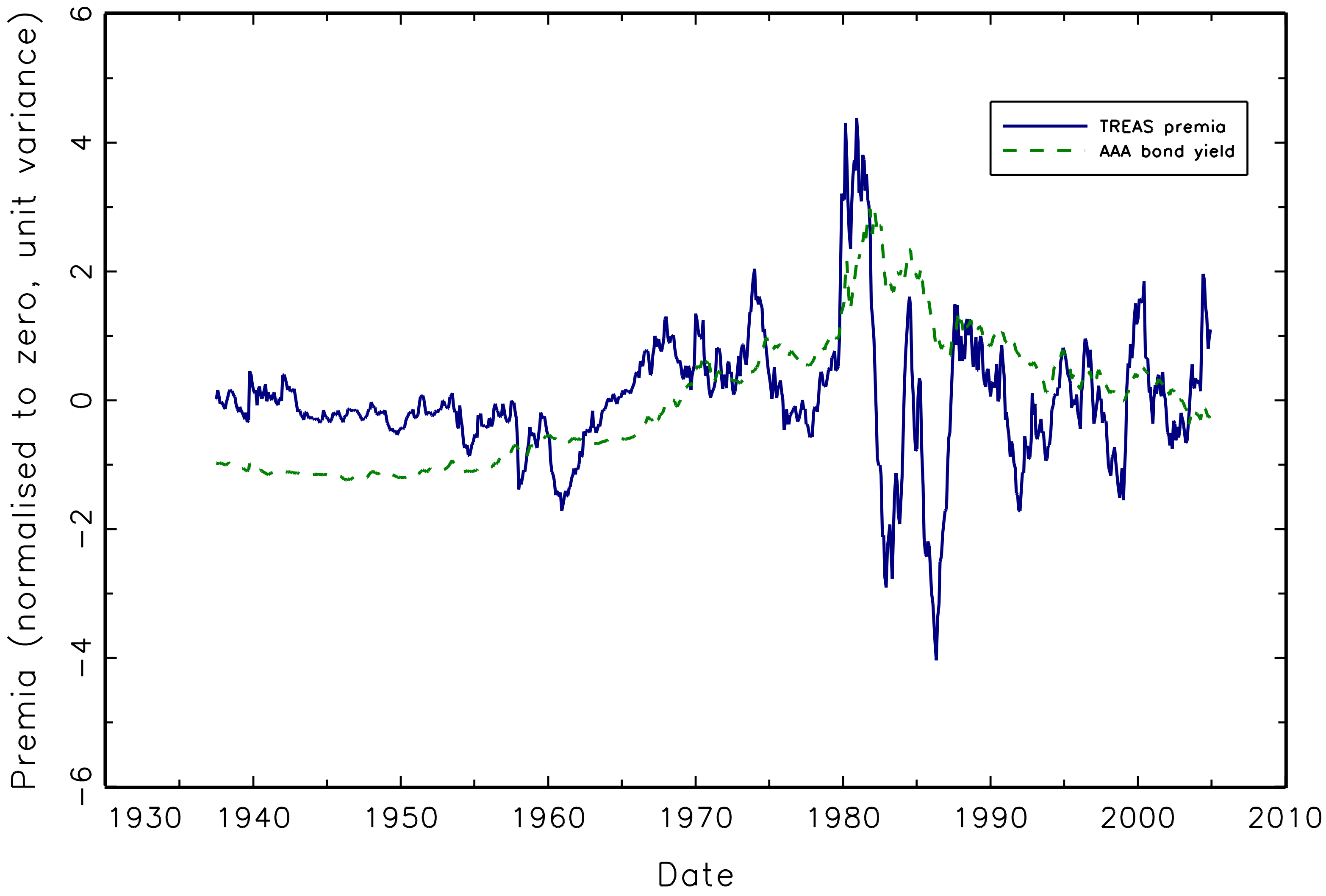


Figure 4: Comparison of the estimated treasury risk premium and the AAA bond yield (recent subsample)

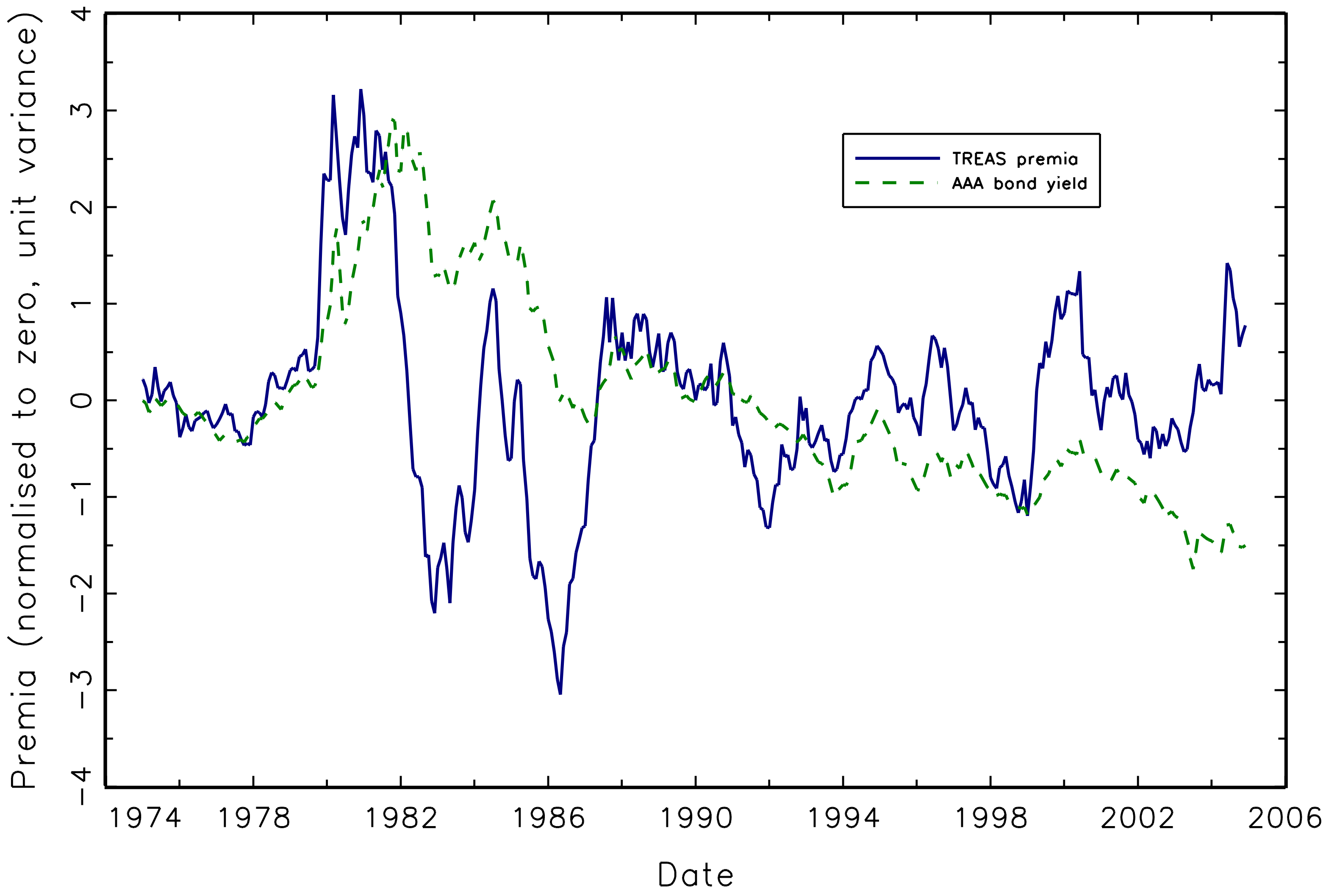
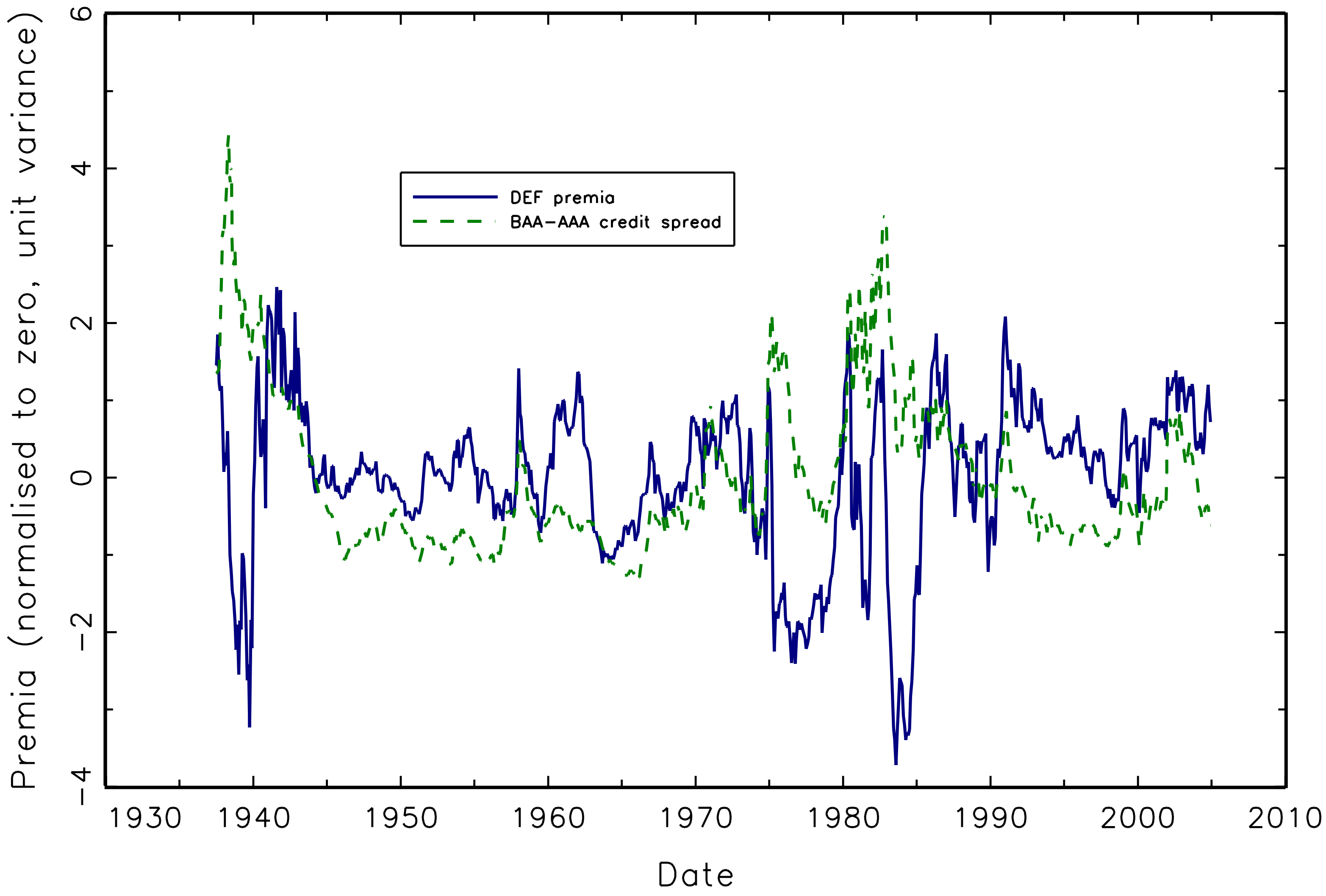


Figure 5: Comparison of estimated default risk premium and the Baa–Aaa yield spread



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