The Determinants of Stock and Bond Return Comovements*

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Abstract

We study the economic sources of stock-bond return comovement and its time variation using a dynamic factor model. We identify the economic factors employing structural and non-structural vector autoregressive models for economic state variables such as interest rates, (expected) inflation, output growth and dividend payouts. We also view risk aversion, and uncertainty about inflation and output as additional potential factors. Even the best fitting economic factor model fits the dynamics of stock-bond return correlations poorly. Alternative factors, such as liquidity proxies, help explain the residual correlations not explained by the economic models.

JEL Classification: G11, G12, G14, E43, E44

Keywords: Factor Models, Stock-Bond Return Correlation, Macroeconomic Factors, New-Keynesian Models, Structural VAR, Liquidity, Flight-to-Safety

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Abstract

We study the economic sources of stock-bond return comovement and its time variation using a dynamic factor model. We identify the economic factors employing structural and non-structural vector autoregressive models for economic state variables such as interest rates, (expected) inflation, output growth and dividend payouts. We also view risk aversion, and uncertainty about inflation and output as additional potential factors. Even the best fitting economic factor model fits the dynamics of stock-bond return correlations poorly. Alternative factors, such as liquidity proxies, help explain the residual correlations not explained by the economic models.

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1 Introduction

Stock and bond returns in the US display an average correlation of about 19 percent during the post–1968 period. A number of models have had a modest degree of success in generating realistic average correlations using economic state variables. Yet, Shiller and Beltratti (1992) under-estimate the empirical correlation using a present value with constant discount rates, whereas Bekaert, Engstrom, and Grenadier (2005a) over-estimate it in a consumption-based asset pricing model with stochastic risk aversion.

The substantial time variation the stock-bond return correlation displays is undoubtedly a more puzzling empirical phenomenon. Over our sample period, we identify one 5-year episode in which the stock-bond return correlation was as high as 75 percent, and one in which it dropped to lower than minus 60 percent. There is a growing literature documenting this time variation using sophisticated statistical models (see Guidolin and Timmermann (2004)), but much less work trying to disentangle its economic sources. In particular, the negative stock–bond return correlations observed since 1998 are mostly ascribed to a "flight-to-safety" phenomenon (see e.g. Connolly, Stivers, and Sun (2005)), where increased stock market uncertainty induces investors to flee stocks in favor of bonds.

This article asks whether a dynamic factor model in which stock and bond returns depend on a number of economic state variables can explain the average stock-bond return correlation and its variation over time. Our economic state variables do not only include interest rates, inflation, output growth and cash flow growth, but also a "fundamental" risk aversion measure derived from consumption growth data based on Campbell and Cochrane (1999) and macro-economic uncertainty measures derived from survey data on inflation and GDP growth expectations. The latter variables may reflect true economic uncertainty in the sense of the models of Ribeiro and Veronesi (2002) and David and Veronesi (2004), or heteroskedasticity as in Bansal and Yaron (2004) and Bekaert, Engstrom, and Xing (2005b).

We specify a number of different dynamic models for the economic state variables, including vector autoregressions (VARs) with state-dependent volatilities and regime-switching VARs. We consider non-structural versions of the state variable models and a model with structural restrictions inspired by recent standard New-Keynesian models. Time variation in stock and bond return correlations follows from either the heteroskedasticity present in the state variable model (and identified only from economic state variable data) or, in some specifications, from time variation in factor exposures. We then analyze how well such models fit stock and bond return comovements, characterizing how much of the correlation can be ascribed to economic state variables. For example, the lower variability of inflation and output growth observed since the mid-1980s, the so-called Great Moderation (Blanchard and Simon (2001)), could conceivably lead to lower correlations between stock and bond returns. Whether its timing actually helps matching the time variation in the stock-bond return correlations, including negative correlations at the end of the nineties, remains to be seen.

The remainder of this paper is organized as follows. Section 2 develops a purely statistical bivariate conditional volatility model that produces conditional correlations to serve as a benchmark for the implied correlations from the dynamic economic factor model. Section 3 describes this factor model in more detail and develops the structural and non-structural state variable models used to identify the economic factors. Section 4 details the estimation procedure and the model selection criteria. Section 5 reports the results for the economic factor models. We find that models with time-varying factor exposures and regime-switching dynamics that capture the Great Moderation best fit bond and stock return correlations. While a 8-factor model using the macro-economic uncertainty variables marginally has the best fit, it is fair to say that the fit of all models is rather poor. Section 6 reports a number of robustness checks, which do not change that conclusion. In Section 7, we show that non-macro variables, such as liquidity proxies and stock market uncertainty, help explain the residual correlations. A final section concludes.

2 Regime-Switching Analysis of Stock and Bond Returns

The dynamic factor model we introduce in Section 3 generates fundamentally-driven conditional correlations between stock and bond returns at each point in time. We cannot directly assess and compare the fit of the various factor models with the data because the true conditional correlation is essentially unobserved. While we conduct a number of indirect tests to assess the performance of the various factor model specifications, this section creates an empirical proxy for the true conditional correlation, using a flexible statistical conditional time series model that hopefully captures the time variation in correlations well.

To estimate various candidate models, we obtained daily and quarterly US data over the period 1968Q4-2004Q4 from CRSP. For stock returns, we use NYSE-AMEX-NASDAQ value-weighted returns including dividends from the CRSP Stock File Indices. For the bond market returns, we use returns on 10-year government bonds taken from the CRSP US Treasury and Inflation module. The returns are in excess of the US 3-month T-bill rate. Further details on the data are in Appendix A.

Our analysis is mostly at a quarterly frequency. This is the frequency at which data on the economic state variables used in the dynamic factor models are available, and may also be the highest frequency at which a fundamentals based model is expected to have explanatory power. Nevertheless, we first characterize the variation in stock-bond return correlations using daily return data to calculate ex-post quarterly correlations[1]. Figure 1 plots these correlations over time. While they are (modestly) positive for most of the time, their variation over time is substantial. Correlations were at slightly positive levels in the 1970s, but rose to relatively high levels (about 40%) for most of the 1980s and 1990s. This period of high correlations ended quite abruptly at the end of 1998 when a period of often very negative stock-bond return correlations started. Figure 1 also shows that stock and bond return correlations tend to be quite persistent, an important feature any empirical model should match.

To generate conditional correlations comparable with correlations from the dynamic factor model, we consider a number of alternative conditional models. Table 1 provides a list of the models we estimate. They include bivariate BEKK models (see Engle and Kroner (1995)), a number of regime-switching normal models building on Guidolin and Timmermann (2004), regime-switching models that incorporate ARCH effects (see Cai (1994) and Hamilton and Susmel (1994)), and regime-switching models that use the ex-post quarterly correlations as additional instruments to capture persistence. Because the latter model is - to our knowledge - new to the literature, we describe it in more detail in Appendix B. We subject these models to a battery of specification tests. A first set of tests directly focuses on how well the various specifications perform in modeling the covariance between stock and bond returns. More specifically, we test whether the difference between the model-implied covariance and the product of stock and bond residuals has zero mean and zero autocorrelation (up to an order of 4). We also present a number of heuristic tests, namely the mean absolute difference between the model-implied correlation at time t and the quarterly ex-post correlation at time $t+1$ as well as the R^2 from a regression of the ex-post on the model-implied correlations. Finally, for all models, we also report the Akaike, Schwarz, and Hannan-Quinn information criteria.

Table 2 presents the main specification test results. Panel A reports the covariance specification tests as well as the two heuristic statistics, while Panel B reports the three information criteria. The winning model clearly is model 6, in which both the stock and bond return volatilities as well as their correlation depend on a two-state regime variable and respectively the lagged quarterly ex-post stock (bond) variance and the ex-post correlation. This model is preferred by all information criteria and performs well in the various specification tests. The three-state alternative of this model performs marginally better on the specification tests, but worse on the information criteria (partially because it has 26 instead of 16 parameters for the two-state model) and the heuristic test. Interestingly, the two models including the ex-post volatilities and correlations perform substantially better than those without. A Likelihood Ratio test rejects the null hypothesis that the coefficients on the ex-post measures are zero at the 1 percent level in both models.

For completeness, and because the model is new, Table 3 reports the estimation results for model 6. In Regime 1, which corresponds to the 'normal' regime of positive stock-bond return correlations, stock-bond return variances and correlations are significantly positively related to their (lagged) ex-post counterpart. For the equity (bond) market variance, the coefficient on the past realized variance is substantially (slightly) above one, but the persistence coefficient is below one (about 0.59) for conditional stock-bond return correlations. Regime 2 is observed during episodes of negative stock-bond return correlation. Within this regime, the ex-post measures lose all their explanatory power. Both regimes are highly persistent and have an expected duration of respectively 53 and 20 quarters. Panel A of Figure 1 plots the data-implied conditional correlations together with the quarterly ex-post correlations. Clearly, the conditional correlation shows a similar (but not identical) time series pattern to that of the realized correlations. The most obvious exception is the period after the 1987 crash, during which the ex-ante correlations are - contrary to the ex-post correlations - highly negative. This may simply be a manifestation of the effects of the crash dissipating faster than expected. This contrasts with the post

1998 period when both the ex-ante and ex-post correlations drop to strongly negative values.

3 Dynamic Stock and Bond Return Factor Model

In this section we present the general factor model linking stock and bond returns to structural factors. Section 3.1 considers the dynamic factor model. Section 3.2 discusses the models for the economic state variables.

3.1 The Dynamic Factor Model

3.1.1 Constant Beta Factor Model

Let $r_{s,t}$ denote the excess stock return and $r_{b,t}$ the excess bond return. We assume the following dynamics for $r_t = (r_{s,t}, r_{b,t})'$:

$$r_t = E_{t-1}(r_t) + \beta'_{t-1} F_t + \varepsilon_t \tag{1}$$

where $E_{t-1}(r_t)$ represents the expected excess return vector, $\beta_{t-1} = (\beta_{s,t-1}, \beta_{b,t-1})$ is a $n \times 2$ matrix of respectively stock and bond return factor loadings, and F_t is a $n \times 1$ vector containing the structural factors. The vector $\varepsilon_t = (\varepsilon_{s,t}, \varepsilon_{b,t})'$ represents return shocks not explained by the economic factors. The factors F_t represent innovations to the fundamental state variables X_t, i.e.

$$F_t = X_t - E_{t-1}(X_t)$$

with

$$F_t \sim N\left(\mathbf{O}, \Sigma_t\right).$$

Σ_t is a $n \times n$ diagonal matrix containing the conditional variances of the structural factors, which are potentially time-varying. The off-diagonal elements are zero as we enforce structural factors to be orthogonal.

Because our focus is on second moments, we do not further explore the implications of the factor model for expected returns. We simply model expected returns as constants but investigate the robustness of our results to this assumption in Section 6. Under the null of the model, the covariance matrix of the stock and bond return residuals is homoskedastic and diagonal. We denote the residual variance by h_s and h_b, respectively. The betas $\beta_{s,t-1}$ and $\beta_{b,t-1}$ are the sensitivities of respectively stock and bond returns to shocks in the economic state variables. The benchmark model forces these betas to be constant, i.e. $\beta_{s,t-1} = \beta_s$, $\beta_{b,t-1} = \beta_b$. Simple affine pricing models imply that stock and bond return innovations are constant beta functions of the innovations in the state variables. Similarly, linearized versions of many present value models for equity pricing (see e.g. Campbell and Ammer (1993) and Bekaert, Engstrom, and Grenadier (2005a)) imply a similar constraint on the betas. We discuss some economic reasons for time variation in the betas in Section 3.1.3.

The factor model implies that the comovement between stock and bond returns follows directly from their joint exposure to the same economic factors. The conditional covariance can be written as:

$$cov_{t-1}\left(r_{s,t}, r_{b,t}\right) = \beta_s' \Sigma_t \beta_b.$$

Hence, the sole driver of time variation in the covariance between stock and bond returns is the heteroskedasticity in the structural factors. The betas determine the sign of the covariance. Dividing the covariance by the product of the stock return and bond return volatilities, i.e. $\sqrt{\beta_s' \Sigma_t \beta_s + h_s}$ and $\sqrt{\beta_b' \Sigma_t \beta_b + h_b}$, yields the model-implied conditional correlation between stock and bond returns $\rho_{t-1}\left(r_{s,t}, r_{b,t}\right)$. We can decompose the correlation as follows:

$$\begin{aligned} \rho_{t-1}\left(r_{s,t}, r_{b,t}\right) &= \frac{\beta_s^1 \beta_b^1 var_{t-1}(F_t^1)}{\sqrt{\beta_s' \Sigma_t \beta_s + h_s}\sqrt{\beta_b' \Sigma_t \beta_b + h_b}} + \frac{\beta_s^2 \beta_b^2 var_{t-1}(F_t^2)}{\sqrt{\beta_s' \Sigma_t \beta_s + h_s}\sqrt{\beta_b' \Sigma_t \beta_b + h_b}} \\ &\quad + ... + \frac{\beta_s^n \beta_b^n var_{t-1}(F_t^n)}{\sqrt{\beta_s' \Sigma_t \beta_s + h_s}\sqrt{\beta_b' \Sigma_t \beta_b + h_b}}. \end{aligned} \tag{2}$$

This decomposition clearly shows the standard effects of a linear factor model. First, factors with higher variances have the largest effect on comovement. Second, when the variance of a factor increases, its contribution to the comovement can become arbitrarily large. Third, if bond and stock betas have the same sign, increased factor variances lead to increased comovement, and vice versa. Consequently, to generate the substantial variation in comovements documented in Section 2 in the context of this model, the volatility of the fundamentals must display substantial time variation. Moreover, to generate negative covariances, it must be true that there is at least one factor to which bonds and stocks have opposite exposures, and this factor must at times have substantial relative variance. We now motivate which factors should be included in the factor model from the perspective of rational pricing models.

3.1.2 Economic Motivation for the Factors

In standard rational pricing models, the fundamental factors driving stock and bond returns either affect cash flows, or discount rates. We discuss each in turn.

Cash Flows A crucial difference between stocks and bonds is that stocks have stochastic cash flows (dividends), while bonds have fixed nominal cash flows. As a consequence, inflation is an obvious state variable that may generate different exposures between bond and stock returns. Unfortunately, the discount rate effects of inflation likely dominate the cash flow effects (see below). Any factor highly correlated with the evolution of real dividends should affect stock but not bond returns. Apart from including cash flow growth (dividend growth) directly, we also use the observed and expected output gap (defined as output minus potential output) as additional economic 'cash flow' factors[2]. These macro factors may have discount rate effects too.

Discount Rates (Term Structure Effects) As is well known, the level of interest rates drives most of the variation in bond returns, and we include a short-term interest rate as a factor in our model. For long-term bonds, the relevant state variable is the long-term interest rate, which can in turn be decomposed into a short-term real rate, a term premium, expected inflation and an inflation risk premium. Increases in all these 4 components unambiguously decrease bond returns. While exposure to real rates and term premiums may induce positive correlation between bond and stock returns, because equities represent a claim on real assets the discount rate on stocks should not depend on nominal factors such as expected inflation. However, the Mundell-Tobin model states that high expected inflation raises the opportunity cost of money, causing people to switch from money to interest-bearing and real assets. This switch may drive down real rates and induce a negative correlation between real rates and expected inflation. This in turn may imply a positive correlation between stock returns and (expected) inflation shocks. Yet, a recurring finding is that stocks seem to be very poor hedges against inflation and their returns correlate negatively with inflation shocks and expected inflation (see e.g. Fama and Schwert (1977)). To identify the term structure components of discount rates, we introduce inflation, expected inflation, and the short-term nominal interest rate as state variables[3]. Finally, note that measures correlated with expected output growth may reflect information about real rates as well and hence induce positive correlation between stock and bond returns.

Discount Rates (Risk Premiums) We use measures of economic uncertainty and risk aversion to capture stock and bond risk premia. For instance, Bekaert, Engstrom, and Grenadier (2005a) show that stochastic risk aversion plays an important role in explaining positive stock-bond return correlations. The effects of risk aversion are, however, quite complex. In the models of Bekaert, Engstrom, and Grenadier (2005a) and Wachter (2006), increases in risk aversion unambiguously increase equity and bond premiums, but their effect on discount rates is actually ambiguous. A rise in risk aversion may increase the real interest rate through a consumption smoothing effect or decrease it through a precautionary savings effect. Bansal and Yaron (2004) and Bekaert, Engstrom, and Xing (2005b) stress economic uncertainty as a channel that may affect risk premiums and equity valuation. The effect of increases in uncertainty on equity valuation, while often thought to be unambiguously negative, is actually ambiguous as increased uncertainty may lower real interest rates through precautionary savings effects. Hence, an increase in uncertainty may cause bonds and stocks to move in opposite directions depending on the relative strenghts of the term structure and risk premium effects. Cash flow uncertainty is likely correlated with general measures of economic uncertainty, such as uncertainty about GDP growth.

An alternative motivation for the use of uncertainty measures in explaining stock and bond return comovement follows from recent studies by Ribeiro and Veronesi (2002) and David and Veronesi (2004). They show that higher uncertainty about future economic state variables makes investors' expectations react more swiftly to news, affecting both variances and covariances of asset returns.

Because we try to disentangle economic sources of comovements from potentially behavioral ones, we use a measure of risk aversion that is tied tightly to economic fundamentals, taken from Bekaert and Engstrom (2006). They create an empirical proxy for risk aversion, based on the external habit specification of Campbell and Cochrane (1999). The risk aversion measure is generated solely by past consumption growth data, and tends to behave counter-cyclically. To capture economic uncertainty, we use the survey of professional forecasters to create measures of inflation, output gap, and cash flow growth uncertainty. The data appendix provides full details.

Eventually we retain the following economic state variables: output gap (y_t), inflation (π_t), expected future output gap (ye_t), output uncertainty (yd_t), expected inflation (πe_t), inflation uncertainty (πd_t), nominal interest rate (i_t), cash flow growth (cg_t), cash flow uncertainty (cgd_t) and risk aversion (fra_t), for a total of 10 state variables.

3.1.3 Is There Time Variation in the Betas?

Because time variation in the betas could spuriously pick up non-fundamental sources of comovement, we significantly limit the state dependence of the betas. Yet, there certainly are reasons to expect betas to be time-varying. First, because we use a constant maturity bond portfolio, interest rate changes affect the duration of the portfolio and consequently its interest rate sensitivity. As interest rates increase, the bond portfolio's lower duration should decrease its sensitivity to interest rate shocks. This line of thought applies to stocks as well, as stocks are long-duration assets with stochastic cash flows. The duration of stock returns actually depends on its dividend yield. We therefore allow the betas of stocks with respect to interest rate shocks to be a function of the level of the (log) payout ratio denoted by dy_t. Unfortunately, it is conceivable that behavioral factors may indirectly account for the resulting time variation in betas, if they are correlated with valuation effects reflected in payout ratios. Second, economic uncertainty may not only affect the heteroskedasticity in the fundamental factors (see section 3.2), but also the betas. In the model of David and Veronesi (2004), widening the dispersion in beliefs increases the effect of economic shocks on returns. Our measures of inflation and output uncertainty can be viewed as proxies to belief dispersion regarding inflation and economic growth expectations. Hence, we let the sensitivity to inflation, output gap and cash flow growth shocks be a function of respectively inflation, output and cash flow uncertainty. In the model of Bekaert, Engstrom, and Xing (2005b), the variability of risk aversion increases as risk aversion increases. Consequently, in the model with risk aversion, we let the exposure to risk aversion shocks be a function of (lagged) risk aversion itself.

Summarizing, we assume:

$$\begin{aligned}
\beta^k_{s(b),t-1} &= \beta^k_{s(b),0} + \beta^k_{s(b),1} yd_{t-1} \\
\beta^j_{s(b),t-1} &= \beta^j_{s(b),0} + \beta^j_{s(b),1} \pi d_{t-1} \\
\beta^i_{s,t-1} &= \beta^i_{s,0} + \beta^i_{s,1} dy_{t-1} \\
\beta^i_{b,t-1} &= \beta^i_{b,0} + \beta^i_{b,1} i_{t-1} \\
\beta^{cg}_{s(b),t-1} &= \beta^{cg}_{s(b),0} + \beta^{cg}_{s(b),1} cgd_{t-1} \\
\beta^{fra}_{s(b),t-1} &= \beta^{fra}_{s(b),0} + \beta^{fra}_{s(b),1} fra_{t-1}
\end{aligned}$$

for $k = y, ye, yd$ and $j = \pi, \pi e, \pi d$.

3.2 The State Variable Model

This section explains the specification of the models for the fundamental state variables, which leads to the identification of the structural factors F_t. Let $X_t = [y_t, \pi_t, ye_t, yd_t, \pi e_t, \pi d_t, i_t, cg_t, cgd_t, fra_t]'$. The general model has the following form:

$$X_t = \mu + AX_{t-1} + \Gamma_t F_t \tag{3}$$

with $F_t \sim N(0, \Sigma_t)$. Σ_t is a $n \times n$ diagonal stochastic covariance matrix, implying that the structural shocks or factors F_t are uncorrelated, conditional on time $t-1$ information (see below). Γ_t is a $n \times n$ matrix of structural parameters, capturing the contemporaneous correlation between the fundamental state variables. The $n \times n$ matrix A captures the feedback in the state variables, and we denote the drift by the $n \times 1$ vector μ[4].

Our modeling of Σ_t is inspired by direct empirical evidence of changing fundamental variances. Macroeconomists have noted a downward trend in the volatility of output growth and inflation from 1985 onwards (see e.g. Stock, Watson, Gali, and Hall (2003) and Blanchard and Simon (2001)), a phenomenon known as the Great Moderation. Monetary economists debate the effects of heteroskedasticity in the fundamental shocks versus shifts in monetary policy on the identification of economic and monetary policy shocks (see e.g. Cogley and Sargent (2005) and Sims and Zha (2005)).

Consequently, we consider four different models for the variance matrix Σ_t. First, we consider a homoskedastic volatility model as a benchmark but likely misspecified model. In a second model, the state-dependent volatility model, we allow the factor variances to depend on the own lagged state variables X_{t-1}. There is a long tradition in finance to use state-dependent volatility models (see e.g. Cox, Ingersoll, and Ross (1985)), but it is less common in macroeconomics (see Evans and Wachtel (1993) though for a related inflation volatility model). The third model, the regime-switching volatility model, allows the volatilities of the structural factors to be driven by a latent regime variable S_t. The regime variable can capture structural changes in the variance of fundamental shocks as identified for instance by Sims and Zha (2005) and Ang, Bekaert, and Wei (2007b) and/or the Great Moderation phenomenon. Our final model, the regime-switching state-dependent volatility model, includes both lagged state variables and regime-switching variables. In summary, we have the following models:

Model	**Specification**
Homoskedastic Volatility Model	$\Sigma_t = \Sigma$
State-dependent Volatility Model	$\Sigma_t = \Sigma(X_{t-1})$
Regime-Switching (RS) Volatility Model	$\Sigma_t = \Sigma(S_t)$
RS State-dependent Volatility Model	$\Sigma_t = \Sigma(X_{t-1}, S_t)$.

In modelling S_t, we follow Bikbov (2005), and use three different regime variables in the most general version of our model. One variable, s_t^{ex} shifts the volatility of the exogenous shocks, like output gap and inflation shocks[5]. A second variable s_t^{ir} affects the volatility of the interest rate shock, i.e. the monetary policy shock. The third variable s_t^{m} either switches certain structural parameters contained in Γ_t, which we discuss below, or shifts the volatility of cash flow growth shocks or risk aversion shocks. In summary, we have $S_t = \{s_t^{ex}, s_t^{ir}, s_t^{m}\}$. To retain tractability, we assume the three regime variables to be independent Markov chain processes. In most cases, the regime variable can take on two values with the transition probabilities between states assumed constant.

Finally, modeling Γ_t leads to the actual identification of the factors in equation (3). To accommodate a structural identification, we first consider a simple model with just three state variables: the output gap y_t, inflation π_t and the nominal interest rate i_t. These are the variables typically used in New-Keynesian models to identify respectively demand shocks, supply shocks and monetary policy shocks. By imposing restrictions from a state-of-the-art New-Keynesian macro model, we obtain a structural interpretation of the various shocks identified through the model. We also considered the three state variable model, identified non-structurally through a simple Choleski decomposition using the ordering $X_t = [y_t, \pi_t, i_t]'$. This model performed worse than the structural model and we do not report on it further. We do consider an extension of this non-structural model where risk aversion is added as a state variable. We order risk aversion last, so that the risk aversion shock is purged of the other fundamental shocks. Finally, we consider a model with 8 state variables: $X_t = [y_t, \pi_t, ye_t, yd_t, \pi e_t, \pi d_t, i_t, cg_t]'$. In this model, we identify the shocks through a Choleski decomposition using the order indicated above. Consequently, in this model the uncertainty measures proxy for bond and equity risk premiums. We do not consider models that combine both risk aversion and uncertainty measures, as our risk aversion and inflation uncertainty measures are 63 percent correlated.

We now discuss the three different state variable models in more detail.

3.2.1 Three State Structural VAR Model

The three variable model should lead to the identification of three structural shocks F_t^y, F_t^π and F_t^i, respectively the output, inflation and interest rate shock. To do so, we use a standard New-Keynesian three-equation model (see e.g. Bekaert, Cho, and Moreno (2006)) comprising an IS or demand equation, an aggregate supply (AS) equation, and a forward looking monetary policy rule:

$$y_t = a_{IS} + \mu E_t(y_{t+1}) + (1-\mu)\, y_{t-1} - \phi\left(i_t - E_t\left(\pi_{t+1}\right)\right) + F_t^y \tag{4}$$

$$\pi_t = a_{AS} + \delta E_t(\pi_{t+1}) + (1-\delta)\, \pi_{t-1} + \lambda y_t + F_t^\pi \tag{5}$$

$$i_t = a_{MP} + \rho i_{t-1} + (1-\rho)\left[\beta(s_t^m) E_t\left(\pi_{t+1}\right) + \gamma(s_t^m) y_t\right] + F_t^i. \tag{6}$$

The μ parameter and δ parameter represent the degree of forward-looking behavior in the IS and AS equations and if they are not equal to one the model features endogenous persistence. The ϕ parameter measures the impact of changes in real interest rates on output and λ the effect of output on inflation. They are critical parameters in the monetary transmission mechanism, and high and positive values imply that monetary policy has significant effects on the real economy and inflation. Because all these parameters arise from micro-founded models, for example representing preference parameters, we assume them to be time invariant. The monetary policy rule is the typical forward-looking Taylor rule with smoothing parameter ρ. However, as in Bikbov (2005), we allow systematic monetary policy to vary with a regime variable. There is substantive evidence that monetary policy has gone through activist and more accommodating spells (see e.g.

Cho and Moreno (2006), Boivin (2005)). This structural model provides an economic interpretation to the contemporaneous relations between the state variables and a natural identification of the shocks F_t^y, F_t^π and F_t^i. We furthermore specify the general regime-switching state-dependent volatility model for the three factors as follows:

$$\begin{aligned} var(F_t^y \,|X_{t-1}, S_t) &= \exp(\alpha_y(s_t^{ex}) + \theta_{1,y} y_{t-1} + \theta_{2,y} yd_{t-1}) &(7)\\ var(F_t^\pi \,|X_{t-1}, S_t) &= \exp(\alpha_\pi(s_t^{ex}) + \theta_{1,\pi} \pi_{t-1} + \theta_{2,\pi} \pi d_{t-1}) &(8)\\ var(F_t^i \,|X_{t-1}, S_t) &= \exp(\alpha_i(s_t^{ir}) + \theta_i i_{t-1}). &(9)\end{aligned}$$

The exponential function guarantees non-negative volatilities. Here, yd_{t-1} and πd_{t-1} are respectively output uncertainty and inflation uncertainty (as measured by the survey forecasts). Hence, we relate the volatility of the output and inflation factors to the uncertainty about its forecast. Further, the variance of each of the state variables depends on the lagged state variable level and on a regime variable. As mentioned before, we differentiate between a variable s_t^{ex} affecting the volatility of exogenous shocks and a variable s_t^{ir} affecting the volatility of interest rate shocks The homoskedastic, state-dependent, and regime-switching volatility models are obvious special cases of the model outlined in equations (7) to (9).

While it is theoretically possible to obtain the rational expectations solution of the model in equations (4)-(6), the model implies highly non-linear restrictions further complicated by the presence of regime-switching and heteroskedasticity in the structural shocks. Bikbov (2005) estimates a slightly simpler version of this model adding term structure data and notes that without these additional data the identification of the regimes is rather poor. Our strategy is different. We replace the forward-looking rational expectations with our survey forecast measures for expectations[6]. More specifically, we assume $E_t\left(X_{t+1}\right) = X_t^f$ with X_t^f the median of the individual survey forecasts for the different state variables. Using these forecasts, we write the model in compact matrix notation as

$$B_{11} X_t = \alpha + A_{11} X_t^f + B_{12} X_{t-1} + F_t, \qquad F_t \sim N(0, \Sigma_t)$$

where

$$\mathbf{B}_{11} = \begin{bmatrix} 1 & 0 & \phi \\ -\lambda & 1 & 0 \\ -\left(1-\rho\right)\gamma(s_t^s) & 0 & 1 \end{bmatrix}, \mathbf{A}_{11} = \begin{bmatrix} \mu & \phi & 0 \\ 0 & \delta & 0 \\ 0 & \left(1-\rho\right)\beta(s_t^s) & 0 \end{bmatrix}, \mathbf{B}_{12} = \begin{bmatrix} 1-\mu & 0 & 0 \\ 0 & 1-\delta & 0 \\ 0 & 0 & \rho \end{bmatrix}$$

leading to the following reduced form:

$$X_t = c + \Omega_1 X_t^f + \Omega_2 X_{t-1} + \Gamma F_t$$

with $c = B_{11}^{-1}\alpha, \Omega_1 = B_{11}^{-1}A_{11}, \Omega_2 = B_{11}^{-1}B_{12}$, $\Gamma = B_{11}^{-1}$, and Σ_t the diagonal conditional covariance matrix described in equations (7)-(9).

This model can be estimated using limited maximum likelihood (we do not specify the dynamics of ye_{t-1} and πe_{t-1}). The use of the survey forecasts therefore both adds additional information and permits to identify the structural parameters with a relatively easy and straightforward estimation procedure. The quality of the model identification depends to a large extent on the quality of the survey forecasts. While there is not much evidence on the quality of the GDP growth survey forecasts, which we use to forecast the output gap, a recent paper by Ang, Bekaert, and Wei (2007a) suggests that the median survey forecast of inflation is the best inflation forecast out of sample, beating time series, Philips curve and term structure models.

There is definitely controversy about what constitutes an adequate empirical proxy for the output gap. While our initial model uses a quadratic trend to measure potential output, the robustness section considers alternative output gap measures and also uses GDP and consumption growth as state variables in non-structural versions of the three state variable model.

3.2.2 Four State Non-Structural VAR Model with Risk Aversion

The four variable model should lead to the identification of four structural shocks F_t^y, F_t^π, F_t^i and F_t^{fra}, respectively the output, inflation, interest rate and risk aversion shock. To do so, we use a Choleski decomposition with the ordering $X_t = [y_t, \pi_t, i_t, fra_t]'$. The matrix Γ_t is assumed to be lower-triangular, allowing identification of the shocks. While it seems natural to rank the interest rate last but one, this ordering is to a certain extent arbitrary. The ordening implies that F_t^π represents inflation shocks not correlated with output, while F_t^i represents an interest rate shock cleansed of the influence of inflation and the output gap. Similarly, the risk aversion shock represents a shock that is corrected for contemporaneous correlation with the output gap, inflation and the interest rate. Consequently, some of its cyclical properties may have disappeared.

The variance model concretely consists of:

$$
\begin{aligned}
var(F_t^y\,|X_{t-1}, S_t) &= \exp(\alpha_y(s_t^{ex}) + \theta_{1,y}y_{t-1} + \theta_{2,y}yd_{t-1}) \\
var(F_t^\pi\,|X_{t-1}, S_t) &= \exp(\alpha_\pi(s_t^{ex}) + \theta_{1,\pi}\pi_{t-1} + \theta_{2,\pi}\pi d_{t-1}) \\
var(F_t^i\,|X_{t-1}, S_t) &= \exp(\alpha_i(s_t^{ir}) + \theta_i i_{t-1}) \\
var(F_t^{fra}\,|X_{t-1}, S_t) &= \exp(\alpha_{fra}(s_t^m) + \theta_{fra}fra_{t-1}).
\end{aligned}
$$

The risk aversion factor variance is a loglinear function of lagged risk aversion in case of the state-dependent volatility specifications. The regime-switching volatility specifications allow the risk aversion factor variance to switch according to a seperate regime variable, s_t^m. In a specification analogous to the structural model, we let the interest rate coefficients in Γ_t depend on a regime variable. However, it proved difficult to disentangle regimes in Γ_t and Σ_t, so we abandoned this effort.

3.2.3 Eight State Non-Structural VAR Model

For the eight state non-structural model, we use the Choleski ordening $X_t = [y_t, \pi_t, ye_t, yd_t, \pi e_t, \pi d_t, i_t, cg_t]'$. That is, we rank the expectation measures and their uncertainty after the output gap and inflation, so that these shocks reflect information that is not present in contemporaneous observed macro information. The cash flow growth shock is purged of all contemporaneous macro-economic influences, including the interest rate. We again assume Γ_t to be lower-triangular and constant. We use an additional regime swiching variable, s_t^m, for the cash flow growth variance. Whereas the variances of y_t, π_t and i_t are modeled as is 3.2.2, we also have

$$
\begin{aligned}
var(F_t^{ye}\,|X_{t-1}, S_t) &= \exp(\alpha_{ye}(s_t^{ex}) + \theta_{1,ye}ye_{t-1} + \theta_{2,ye}yd_{t-1}) \\
var(F_t^{yd}\,|X_{t-1}, S_t) &= \exp(\alpha_{yd}(s_t^{ex}) + \theta_{yd}yd_{t-1}) \\
var(F_t^{\pi e}\,|X_{t-1}, S_t) &= \exp(\alpha_{\pi e}(s_t^{ex}) + \theta_{1,\pi e}\pi e_{t-1} + \theta_{2,\pi e}\pi d_{t-1}) \\
var(F_t^{\pi d}\,|X_{t-1}, S_t) &= \exp(\alpha_{\pi d}(s_t^{ex}) + \theta_{\pi d}\pi d_{t-1}) \\
var(F_t^{cg}\,|X_{t-1}, S_t) &= \exp(\alpha_{cg}(s_t^m) + \theta_{1,cg}cg_{t-1} + \theta_{2,cg}cgd_{t-1}).
\end{aligned}
$$

The variances of expected output growth and expected inflation are modeled using both the lagged state variable and the aggregate lagged uncertainty measures as instruments. The variances of the uncertainty measures depend on their own lag. The variance of cash flow growth depends both on its own lag and on lagged cash flow uncertainty. All variance specifications have a regime-switching constant, but the regime variables s_t^{ir} and s_t^{m} in the interest rate and cash flow equations differ from the one present in the specifications for the other variables.

Because the volatility of (expected) output and inflation uncertainty shocks shifts with s_t^{ex}, one could expect the uncertainty measures, which are highly correlated with true heteroskedasticity, to exhibit a mean shift. That is, μ^{yd} and $\mu^{\pi d}$ should depend on s_t^{ex} as well. While we do not allow this dependence in the initial specification, we assess its importance in the robustness section.

4 Estimation and Model Selection

4.1 Model Estimation

We follow a two-stage procedure to estimate the bivariate model presented in equation (1). In a first stage, we estimate the state variable model using maximum likelihood. In a second step, we estimate the factor model conditional on the economic factor shocks identified in the first step. Under the null of the model, the covariance between stock and bond returns is captured by their joint exposure to the economic factor innovations, therefore there is no loss in efficiency from estimating the stock and bond return equations seperately.

From an econometric point of view, it would be more efficient to estimate the factor and state variable models in one step. The goal of our article, however, necessitates a two-step estimation. An important risk of a one-step estimation procedure is that the parameters of the state variable model are estimated to help accommodate the conditional stock-bond return correlation, which would make the economic interpretation of the factors problematic.

We estimate the structural model using limited-information maximum likelihood because we replace unobservable conditional expected values by observable measures based on survey forecasts. For the non-structural state variable models we use full-information maximum likelihood.

To choose the optimal number of lags in these reduced-form VARs, we use the Schwarz criterion. The criterion selects one lag for the four and eight variable state models. The eight state variable model is still likely to be over-parameterized. We impose further restrictions on the parameter matrix A as follows. We obtain consistent estimates of the feedback coefficients using OLS, and compute White (1980) heteroskedasticity-consistent standard errors for the coefficients. We then set coefficients with a t-statistic lower than one equal to zero in the maximum likelihood estimation.

4.2 Model Selection

To determine which of the different models best fits stock-bond return correlations, we investigate a number of selection criteria.

First, we conduct specification tests on the estimated cross-product of the stock and bond residuals, $\hat{z}_t = \hat{\varepsilon}_{s,t}\hat{\varepsilon}_{b,t}$, for each model. Under the null hypothesis that the model is correctly specified and captures stock-bond return comovements, we have

$$E\left[\hat{z}_t\right] = 0 \tag{10}$$

$$E\left[\hat{z}_t \hat{z}_{t-k}\right] = 0, \text{ for } k = 1, ..., \tau. \tag{11}$$

The former is a zero mean test and verifies if the model fits the average level of the comovement between stock and bond returns. The latter tests whether there is serial correlation left in the cross residuals. Serial correlation indicates that the model does not capture the time variation in the comovements. To maintain sufficient power, we only use $\tau = 2$ and $\tau = 4$. We test the validity of these orthogonality conditions within a GMM framework.

Second, we compare our model-implied conditional correlations, calculated through equation (2), with the data-implied conditional correlation based on the regime-switching model[7] described and estimated in Section 2. We expect the latter to give us a good picture of how the actual conditional correlations vary through time. Consequently, we compute the mean absolute deviation (MAD) between the model-implied correlation and our proxy for the actual conditional correlation. We compute one additional MAD measure for the model correlations, comparing them to the realized correlations, measured using daily returns of the following quarter. This essentially tests the predictive power of the various models for future correlations.

Third, we expect our factor model to capture the features in the data uncovered in Section 2. Particularly, the stock and bond residuals of a well performing model should not exhibit the regime-switching patterns found in the raw stock and bond returns. Consequently, we use the best performing regime-switching model in Section 2 (Model 6) and evaluate it using the residuals from the various factor models as “data”. If the factor model has managed to fit the patterns in the data, this model should provide a rather poor fit to the residuals. In particlar, the model should no longer uncover clearly seperated regimes. We investigate this by computing the regime classification measure RCM of Ang and Bekaert (2002):

$$RCM = 400 \times \frac{1}{T} \sum_{t=1}^{T} p_t \left(1 - p_t\right)$$

with p_t the smoothed (ex-post) probability of being in state 1 at time t. If no regimes remain, this measure should be close to 100. This means that the regime-switching model cannot distinguish between regimes.

As a final diagnostic, we compute the R^2 of the factor model for respectively stock and bond returns. If the factors fit only a small fraction of the return variance then it is unrealistic to hope for a satisfactory fit for the covariance of stock and bond returns. The literature on stock returns in particular has a long but controversial exponent arguing that stock returns are excessively volatile (see for instance the old debate between Shiller (1981) and Kleidon (1986)).

5 Empirical Results for Models with Macro Variables

This section presents the estimation results for the state variable and dynamic factor models. In the first subsection, we select the best performing state variable models using the specification tests outlined in Section 4.2. Subsections 5.2 and 5.3 present detailed results regarding, respectively, the state variable dynamics and factor exposures of the best models.

5.1 Model Selection Tests

Table 4 presents the model selection tests for the three, the four and the eight factor models in three panels. For each of these models, we consider 8 specifications depending on the beta specification (constant or time-varying) and the volatility specification of the factor shocks (homoskedastic, state-dependent, regime-switching, and a combination of the latter two).

Let us first get a general picture going from Panel A to Panel C. In terms of the residual specification tests, all models remove the serial correlation in the cross product of the residuals, perhaps revealing this to be a not very powerful test. The zero mean test does reject in many cases at the 10% level. The distance measures reveal that no model fits actual conditional correlations (as proxied by our empirical model) particularly well, with the average absolute distance hovering around 40%. The empirical model estimated in Section 2 registered a mean absolute deviation with future realized correlations of 0.241. As would be expected, all models with macro factors perform considerably worse. The benchmark for the RCM statistic is 12.4, the value reached in the raw data. Here, only the 8 factor models with time-varying betas produce substantially higher RCM's suggesting they capture some of the regime-switching behavior of the empirical model.

Within each model, the specification with the time-varying betas and regime-switching volatilities produces the smallest distance measures. These are the models that we will study in a bit more detail in the next two sub-sections. Of these three models, only the 8 factor model fails to reject the null of zero residual covariances at the 10 percent level.

Comparing across models, the best 4 factor and 8 factor models generate substantially lower distance measures than the best 3-factor model. This suggests that time variation in risk aversion and/or uncertainty is a necessary ingredient to understand stock and bond return comovements. While the 8-factor model performs best, the performance of the risk aversion model is notable as it occurs in a parsimonious non-structural model. The non-structural 3-factor model performs much worse than the 3-factor model with structural identification, so augmenting the model with risk aversion is very helpful.

It is conceivable that the relative performance of the various models is linked to how much they explain of bond and stock return dynamics. In the last two columns, we report the R^2 and adjusted R^2 of the various factor models for the stock and bond return equations. Clearly, the macro factors explain much more of bond return variation than they do of stock return variation. The adjusted R^2 for one variant of the 8 factor model for the bond return equation is 36%. For stock returns, the adjusted R^2 is never higher than 12.5%. Clearly, the highest R^2s occur for the 4 and 8 factor models, but only in models with time-varying betas. There the improvement for explaining stock return variation is substantial, often leading to almost twice as high R^2s. Their constant beta variants only do better than the 3 factor counterparts for the bond return equation but far worse for equity.

The distance measures show that the conditional correlations implied by even the best performing factor models are far from the stock-bond return correlation observed in the data. Panel B, C and D of Figure 1 show the conditional correlations implied by the selected three factor, four factor and eight factor models. The three models show a similar pattern generating positive correlations until 1985-1990 (at the time of the Great Moderation), and decreasing and even negative correlations thereafter. While this does not appear to be unlike the pattern observed in the data (see Panel A), both the magnitudes and timing are off. For the three-factor model, the correlations are simply minuscule. For the 4-factor model, the positive correlations observed before 1985 are somewhat too low and the decrease happens way too early. The uncertainty model (8 factors) has similar problems even though the decrease in correlation happens somewhat later, but still earlier than in the data.

5.2 State Variable Dynamics

To conserve space, we report parameter estimates for the 3 retained models in an Appendix (available upon request). We focus the discussion on the identification of regimes and the volatility dynamics of the models as they determine the fundamental stock and bond return correlations. In the New-Keynesian model, the structural parameters are of independent interest but a detailed discussion is beyond the scope of this article[8]. Let us only comment on the regime variable for systematic monetary policy in the interest rate equation. Our β estimates reveal an activist monetary policy regime (with $\beta = 1.9$) and an accommodating monetary policy regime (with β smaller and insignificantly different from 1). The coefficient on the output gap, γ, is only significantly positive in the second regime.

Figure 2 plots the smoothed probabilities for the regime variables for the three different models. All models show significant regime-switching volatility both in statistical and economic terms. Figure 3 then plots the conditional volatilities of the various factors. We discuss the two figures in tandem. We first focus on the regime variable affecting the volatility of the exogenous shocks, i.e. output gap and inflation shocks, in the three factor model. We observe a sudden drop in output and inflation factor volatility in 1984, which corresponds to the start of the Great Moderation. The decreased volatility persists for the remainder of the sample (except for a short period during the 1990 recession), consistent with the Great Moderation representing a permanent structural break. Of course, in our regime-switching model, there is a positive probability that the high volatility regime will re-occur. The identification of this regime is nearly identical in the model with risk aversion. However, the structural model leads to less volatile output shocks. In terms of volatility levels (Figure 3), the non-structural 8 state model is similar to the model with risk aversion, but the time-path of the high volatility regime (Figure 2) is different. The regime variable affecting the volatility of the exogenous shocks in fact coincides with NBER recessions, confirming the counter-cyclical nature of real volatility, noted by Ferson and Merrick (1987) and Kandel and Stambaugh (1990) among others. We also do not observe a sudden drop in output and inflation volatility in 1984, but in 1992. We find that the additional variables, such as the survey-based measures for the expectation and uncertainty regarding the output gap and inflation, are instrumental in the identification of the 'exogenous' regime.

The various models also feature a regime variable capturing the variability of the interest rate shock. For all three models, the high interest rate volatility regime occurs during the 1980-1982 Volcker period. Our estimates indicate that interest rate volatility was about four times as high during the Volcker period as during other periods. This is consistent with the results in Bikbov (2005) who also categorizes the Volcker period as a period of discretionary monetary policy. Unlike Bikbov (2005), our structural model identifies systematic monetary policy to be activist during this period. The model also shows that the 1990 and 2001 recessions were accompanied by an accommodating monetary policy regime, but that activist monetary policy spells became more frequent from 1980 onwards.

In the 4-factor model, the regime variable for risk aversion shocks spikes up during recessions, with the shock volatility approximately doubling relative to normal models. In the 8 variable model, the regime variable affecting the volatility of the cash flow growth shocks appears to capture the permanent structural break in 1984, corresponding to the start of the Great Moderation. The striking fact is that cash flow growth volatility shifts upwards instead of downwards after 1984. Note that this regime variable only applies to cash flow shocks cleansed from macro-economic influences. This finding appears to suggest that idiosyncratic cash flow growth volatility increased as macro-economic uncertainty decreased.

5.3 Factor Beta Exposures

Table 5 presents the beta estimates for the three retained models. Note that the instruments in the beta specification are standardized, so that the betas β_s and β_b are the response to a one standard deviation move in the instrument. We start with the three-factor model. First, for stock returns only the output factor has a beta statistically different from zero, while for bond returns, significance is limited to the interest rate factor. Second, for both stocks and bonds, we find that higher uncertainty regarding output and inflation actually decreases the beta exposures, which is inconsistent with David and Veronesi (2004). Of course, the coefficients are not statistically significant. Third, while we find little statistical evidence for significant time variation in the betas, all three models generate similar time variation in the betas. We graph them for the four-factor model in Figure 4. Note, and this is also true for the three factor model, that the output gap betas for stocks are mostly positive (potentially representing positive cash flow news), while for bonds they are mostly negative (possibly reflecting an interest rate effect). In contrast, the inflation factor is not a source of negative correlation between stock and bond returns as both stocks and bonds have negative inflation betas. Fourth, for the time variation in the interest rate exposures to reflect a duration effect, the coefficients on the payout ratio (for stocks), respectively the interest rate (for bonds), must be negative. While the interest rate exposure of stocks has the correct sign, the coefficient is insignificant, but as Figure 4 shows, the time variation in the interest rate exposure of stocks seems economically significant. Whether this represents a duration effect remains to be seen. It is conceivable that the model simply picks up "unusually" high stock valuations through this channel, with no fundamental interpretation. Alternatively, a positive reaction to real interest rate shocks could be consistent with real rates capturing productivity changes that positively affect stock market valuations. The exposure of bond returns to interest rate shocks is overall negative as expected, but depends positively on the interest rate level, which is inconsistent with a duration effect, complicating a full structural interpretation of the model. This time variation in the exposures to interest rate shocks has important implications for the stock-bond return correlation. As can be seen in Figure 4, during the high correlation period in the second half of the seventies and the eighties, both stock and bond returns react negatively to interest shocks. However, as the payout ratio decreases in the nineties, the exposure of stock returns to interest rate shocks turns positive. The difference between the exposures for stock and bond returns is especially substantial in the 1998-2004 period. This explains some of the negative stock-bond return correlations at the end of the sample period (see Figure 1). Again, all three models share this behavior.

For the four factor model, the factor exposures to the output gap, inflation and the interest rate are qualitatively the same as for the three factor model, with significance (at the 10% level) also concentrated in the interest rate exposures. The coefficient on the payout ratio for the interest rate exposure of stocks is now significant at the 10% level. Of most interest, is the exposure to risk aversion shocks. The exposures of stock and bond returns to shocks in risk aversion are negatively related to the the lagged risk aversion variable, although not significantly, and the constant terms are negative as well. Figure 4 shows that the exposures of stock and bond returns are mostly simultaneously negative. At low levels of risk aversion, the betas sometimes have different signs, implying that the risk aversion factor can potentially generate negative correlations. Whether it will do so also depends on the magnitude of the risk aversion factor variance. Our previous figure on factor volatilities (Figure 3) shows that the variance of the risk aversion factor switches between a high and a low variance state. While recently risk aversion is in the high variance state, it is also a relatively low variance factor. Consequently, it is not surprising that risk aversion fails to generate high negative correlations, as Figure 1 demonstrated. Figure 1 does indicate that the model with risk aversion provides a better fit with the positive correlations before 1987 than the other two models.

The results for the overlapping shocks in the 8-factor model are entirely consistent with the other two models. As to the other factors, there are no significant beta coefficients for the output variables (expected output gap and output uncertainty), but the inflation variables generate some significant effects in the stock return equation. Inflation uncertainty affects both stocks and bond returns negatively. Both the exposures of stock and bond returns to cash flow growth shocks are a positive function of cash flow growth uncertainty. Recall that this shock is cleansed of macro- and interest rate effects. There is a sharp decrease in the cash flow growth uncertainty around 1992, which turns the exposure of stock returns to cash flow growth shocks from mostly positive to mostly negative[9]. The exposure of bond returns is positive and rather stable around 0.15. This helps generate negative correlations between stock and bond returns after 1992, whereas before exposures for both stock and bond returns help explain some of the positive correlations.

6 Robustness

Our fundamentals-based model fails to fit much of the time variation in conditional stock-bond return correlations. There are a number of reasons why our model may not fully explain the data patterns. Section 6.1 explores potential measurement problems for our fundamental state variables. In Section 6.2 we discuss the potential impact of relaxing our assumption of constant expected stock and bond excess returns. Section 6.3 explores the effects of functional form mis-specification and potentially omitted structural changes.

6.1 Measurement Problems

Because there is much disagreement about how to measure the natural rate of output in the New-Keynesian models, we consider two alternative proxies for the output gap: the Hodrick Prescott filtered value of output, and the measure provided by the Congressional Budget Office (CBO). While theoretically we should not use GDP growth in the structural model, we nevertheless also consider a specification with GDP growth replacing the output gap. Finally, we replace GDP growth by consumption growth. The micro foundation for the model builds on a representative agent economy where consumption growth is a state variable, with consumption assumed to equal output (or output plus an i.i.d. shock), a rather heroic assumption.

In our four and eight factor (non-structural) models, we also examine the performance when the output gap is replaced by GDP or consumption growth. In addition, we also re-consider the measurement of economic uncertainty for the eight factor model. Our proxies for output and inflation uncertainty use information from each individual's forecast uncertainty (see the Data Appendix). This measure incorporates both the individual uncertainty about the forecasts and the disagreement in point forecasts (see Giordani and Soderlind (2003) for a discussion). As an alternative, we consider an uncertainty measure only incorporating the disagreement in point forecasts. This is measured as the standard deviation of the real output gap (inflation) forecasts of individual professional forecasters.

Finally, we replace our economic uncertainty measure by a proxy for the conditional volatility of consumption growth. We compute this volatility using a 60-month moving window of data on real consumption growth for non-durables. As shown in the Data Appendix, consumption growth volatility shows a gradual decrease throughout the sample period, consistent with the Great Moderation. However this pattern is reversed from the year 2000 onwards, with a sharp increase in consumption growth volatility during the last 5 years. This phenomenon may well help explain the negative stock-bond return correlation at the end of the sample. In simple consumption-based asset pricing models, consumption growth volatility, just as risk aversion, may potentially have opposite effects on bond and stock returns. An increase in volatility leads to a lower real interest rate through a precautionary savings effect thereby positively affecting both stock and bond returns. However, increased volatility may also drive up equity risk premiums much more than term premiums leading to net exposures that are potentially different across stocks and bonds.

Table 6 reports the model selection tests. The table reveals that the use of alternative output gap measures fails to improve the fit of the three factor model (rows (1) and (2)). The distance measures increase and the R^2 measures decrease. However, there is an improvement of fit using the growth measures, especially using consumption growth (rows (3) and (4)). The improvement in the explanatory power of the factor model for stock returns is particularly dramatic. The improvement in fit appears to arise from the joint positive exposures of stock and bond returns to consumption growth shocks leading to higher correlations on average. In contrast, the distance measures do not improve when alternative growth measures are used in the four (rows (5) and (6)) and the eight factor model (rows (7) and (8)), indicating that the additional information in these alternative output measures is well captured by the existing state variables. Finally, our results do not meaningfully improve when the alternative output and inflation uncertainty measures (row (9)) and consumption growth volatility (row (10)) are used.

6.2 Time-Varying Expected Returns

As Figure 1 shows, the selected factor models tend to under-estimate conditional stock and bond return correlations, on average. They also produce too low unconditional correlations. In the data, this correlation amounts to 19 percent, but the three, four, and eight factor models produce average correlations of respectively 1, 2 and 5 percent. One potential channel to increase unconditional correlations not present in our current model is time variation in expected returns. For instance, in the model of Bekaert, Engstrom, and Grenadier (2005a) risk premiums on stocks and bonds are highly correlated, thus increasing the unconditional correlation between stock and bond returns. In addition, mis-measurement of expected returns may affect the estimation of conditional covariance dynamics. An assumption of constant risk premiums seems particularly strong in light of the important structural shifts in the variances of fundamental variables such as inflation and output growth that we uncovered. Such important changes may lead to abrupt changes in risk premiums, which are unaccounted for in our present models. In fact, Lettau, Ludvigson, and Wachter (2004) recently claim that the decline in macroeconomic volatility may have led to a decline in the equity risk premium.

We consider two extensions to our models to accommodate time variation in expected stock and bond returns. First, we model expected excess returns as a linear function of instruments, including the lagged (log) earnings yield ey_{t-1}, the lagged nominal interest rate i_{t-1}, and the lagged term spread $term_{t-1}$. Second, we use the regime probabilities identified in the structural factor model estimation as instruments for expected returns in univariate regressions.

In Table 7, we report results based on the three factor structural model. Let us first focus on Panel B which shows the conditional mean coefficients. In the instrumental variables regression and using a 10 percent significance level, the earnings yield and the interest rate significantly impact equity risk premiums, whereas the term spread and the interest rate have a positive and significant effect on bond premiums. The coefficient on the equity yield (interest rate) in the equity regression is positive (negative) confirming standard results in the literature. This only leaves the term spread, which has positive coefficients in both regressions, to possibly help generate positive covariation between stock and bond premiums. Structural changes, as identified by the regime variables, do not seem to affect expected stock and bond returns in a meaningful way. In particular, the coefficient on exogenous economic volatility regimes is negative but not significantly different from zero.

In Panel A, we repeat the model selection tests for the new models. Not surprisingly, accommodating structural shifts in expected returns does not improve the fit but accommodating linear predictability leads to lower distance measures, a higher RCM statistic, and higher R^2's for the factor regressions. While this improvement in fit is substantial, the resulting model still performs worse than the 8 factor model. The linear predictability model generates positively correlated risk premiums, so that the unconditional correlation between stock and bond returns increases from 1 to 8 percent.

6.3 Structural Changes

The models in this article only allow for regime-switching behavior in the state variable innovations and their variances. With the exception of a simple version of the New-Keynesian model, the models we estimate are non-structural. In the spirit of the Lucas critique, all parameters should therefore be potentially dependent on the regime variables, including the feedback parameters of the state variable models, the conditional betas and the conditional means of bond and stock returns (see Section 6.2), and even their idiosyncratic variances. For example, the structural downward shift in macroeconomic volatility (the Great Moderation) may translate into lower expected returns and lower systematic stock and bond return variances. However, the long-run variance of stock returns does not seem to have decreased in line with the Great Moderation, which suggests that either betas increased in absolute value or idiosyncratic variances increased. In fact, Campbell, Lettau, Malkiel, and Xu (2001) argue that the idiosyncratic variance of stocks has trended upwards. While it is not yet clear whether this result is robust, one potential reason for the effect may be another structural shift: the post 1995 stock market boom may have led to a larger proportion of younger and more volatile firms to list on stock exchanges.

Accounting for such structural changes must happen in a very controlled manner. For example, it is tempting to accommodate more intricate beta dynamics using a regime-switching beta specification. Unfortunately, such parameter flexibility hampers the structural interpretation of the implied stock-bond return correlation dynamics. Instead, we allow the betas to depend on the three regime variables exogenously extracted from the state variables, without using stock and bond returns.

Table 8 reports the model selection tests for such a specification applied to the eight factor model. The models accommodating structural changes in the betas constitute a significant improvement on the constant beta specification, but they also produce smaller conditional correlation distance statistics than the dynamic beta benchmark model. The best model is the one where betas change with the cash flow growth regime. In this model, the distance statistic drops to 0.322 and the RCM statistic increases to over 30. The explanatory power of the factor model for stock and bond returns increases rather substantially. The main mechanism for the improved fit is a joint positive exposure to cash flow shocks before 1986 that leads to correlations in the 0.4 range. Afterwards, these exposures are mostly opposite in sign for stocks and bonds, contributing to low or even negative correlations. However, the model performs worse than the benchmark model in predicting realized correlations, suggesting that it fails to fit higher frequency correlation dynamics.

In addition, we consider the possibility of a few other exogenously specified breaks for betas. First, a large literature has documented cyclical patterns in risk premiums, Sharpe ratios, and stock betas. Therefore, we estimate a specification in which the betas depend on the NBER recession indicator. Second, we consider the effect of monetary policy regimes using either a dummy for the Volcker period, or for the post-Volcker period. Finally, we consider a break in 1984, a popular date for the onset of the Great Moderation. Table 8 reports the resulting model selection tests. The model with NBER dummies fails to improve upon our dynamic beta specification. The Volcker dummies are a simple way to accommodate monetary policy regimes and are correlated with the s_t^{ir}-specification discussed before. While the post-Volcker period dummy specification is better in some respect, it is not overall better than the s_t^{ir} specification. The same is true for the 1984-break model relative to the s_t^{ex} specification. None of these models improves upon the s_t^m specification, yet they invariably have high explanatory power for the bond and stock return regressions. We also estimated a 8 factor model (not reported) where the intercepts $\left(\mu^{yd}, \mu^{\pi d}\right)$ in the output and inflation uncertainty equations depend on s_t^{ex}. This model's performance is similar to the benchmark model's performance.

7 Liquidity and Flight-to-Safety

Our fundamental factor models fail to fit the extreme range of conditional stock-bond returns correlations. They particularly fail to generate the extremely negative correlations observed since 1998. In this section, we explore some alternative non-fundamental determinants of stock and bond return correlations. First, an often cited non-fundamental explanation for the occasionally observed negative correlations is the flight-to-safety phenomenon, where investors switch from the risky asset, stocks, to a safe haven, bonds, in times of increased stock market uncertainty. This portfolio shift is assumed to cause price changes, and thus implies a negative correlation between stock and bond returns. Connolly, Stivers, and Sun (2005) use the VIX implied volatility measure as a proxy for stock market uncertainty and show that stock and bond return comovements are negatively and significantly related to stock market uncertainty. Second, an exploding literature has stressed the importance of liquidity effects in stock and bond pricing. There is no reason for these liquidity shocks to be perfectly correlated across the two markets and hence "liquidity risk" may be an important omitted variable. Of course, liquidity effects may correlate with the flight-to-safety phenomenon. Crisis periods may drive investors and traders from less liquid stocks into highly liquid Treasury bonds, and the resulting price-pressure effects may induce negative stock-bond return correlations. However, the pricing of liquidity risk may induce positive correlation depending on how stock and bond market liquidity co-move. For example, the monetary policy stance can affect liquidity in both markets by altering the terms of margin borrowing and by alleviating the borrowing constraints of dealers. Existing studies of the commonality in stock and bond liquidity (Chordia, Sarkar, and Subrahmanyam (2005) and Goyenko (2006)) are somewhat inconclusive as to which effect dominates. Finally, if behavioral factors play a role, and individual investors are more prevalent in stock than bond markets, it is possible that a measure of consumer confidence may help explain correlation patterns. In times of high consumer confidence, stocks may be bid up relative to bonds. Of course, such increases in consumer confidence may also be correlated with changes in fundamental risk aversion and the business cycle.

7.1 Test Design and Data

To test whether liquidity, consumer confidence, or flight-fo-safety factors help explain the stock-bond return correlations, we regress the cross product of the residuals from our fundamental model, $\hat{\varepsilon}_{s,t}\hat{\varepsilon}_{b,t}$, on shocks to proxies for liquidity, consumer confidence, and flight-to-safety, denoted by the vector $\varepsilon_{z,t}$:

$$\hat{\varepsilon}_{s,t}\hat{\varepsilon}_{b,t} = \gamma_0 + \gamma_1' \varepsilon_{z,t}.$$

This is basically a specification test verifying whether $cov\left(\varepsilon_{s,t}, \varepsilon_{b,t}\right) = 0$. We take stock and bond return residuals from the best performing eight factor model, but check the robustness of our results to using residuals from the other factor models. We identify the innovations in the liquidity, consumer confidence, and flight-to-safety measures using a VAR of order n, where n is determined using the Schwartz information criterion.

To capture the flight-to-safety phenomenon, we use two measures for stock market uncertainty: the VIX implied volatility (as used by Connolly, Stivers, and Sun (2005)) and the conditional stock return variance as estimated in Section 2. The advantage of the latter instrument is that it is available over the full sample, while the VIX series only starts in 1986. As a proxy for consumer confidence, we use the University of Michigan's Consumer Sentiment Index (see Dominitz and Manski (2004) for a discussion). Our measure of bond market illiquidity is a monthly average of quoted bid-ask spreads across all maturities, taken from Goyenko (2006). As an alternative indicator, we use the on/off the run spread, even though for this indicator we have only data starting in 1994. Our measures of equity market illiquidity use the "zero return" concept developed in Lesmond, Ogden, and Trzcinka (1999), and are taken from Bekaert, Harvey, and Lundblad (2007). They obtain two measures of equity market illiquidity. First, they calculate a capitalization-based proportion of zero daily returns across all firms, and aggregate this proportion over the month. Second, because a zero return does not necessarily mean zero volume, they also calculate the market-cap weighted proportion of zero daily returns on zero volume days within a particular month. Both measures have a positive and high correlation with more standard measures, such as Hasbrouck (2006)'s effective costs and Amihud (2002)'s price impact measures.

With the exception of our equity market volatility measure, all explanatory variables are observed at the monthly frequency. We therefore average them over the quarter before estimating the VAR on quarterly time series.

7.2 Empirical Results

Table 9 reports the estimation results of a regression of the cross product of stock-bond return residuals from the 8 factor model on innovations in the various (combination of) instruments. To conserve space, we do not report detailed estimation results for the VAR[10]. The results are qualitatively similar when residuals from the three and four factor models are used.

Columns 1 and 2 indicate that our fundamental model fails to capture the flight-to-safety phenomenon, as the stock market uncertainty measures have a highly significant, negative effect on the residual correlations[11]. Hence, stock-bond return comovements decrease in times of high stock market uncertainty, confirming the results in Connolly, Stivers, and Sun (2005). Column 3 shows that there is no significant relationship between innovations in consumer confidence and residual stock-bond return comovement. In the next

4 columns, we test whether liquidity helps explaining stock-bond return comovements. Column 4 shows that $\hat{\varepsilon}_{s,t}\hat{\varepsilon}_{b,t}$ is negatively related to the on/off-the-run spread, indicating that stock and bond returns move in opposite directions when bond market liquidity is low. It is conceivable that the on/off the run spread captures more general liquidity conditions, and that the negative sign indirectly reflects a "flight-to-safety" effect. Column 5 shows a positive but insignificant impact of innovations in bond illiquidity on stock-bond return comovements. Poor significance may in part be due to the relatively low quarterly frequency of our dependent variable. The sign is nevertheless consistent with Goyenko (2006). Increases in bond market illiquidity increase expected bond returns, leading to an immediate drop in bond prices. Goyenko (2006) shows that periods of poor bond market liquidity are associated with times of monetary policy tightening, which is in turn bad news for equity markets. Columns 6 and 7 reveal that innovations in equity market illiquidity have a negative impact on residual stock-bond return comovements[12]. This finding is consistent with Goyenko (2006), who finds that stock returns decrease and bond returns increase after a surprise increase in equity market illiquidity. If liquidity is priced in equity markets, an increase in equity illiquidity raises expected returns, leading to an immediate decrease in stock prices. At the same time, a flight-to-liquidity results in a flow of funds into treasuries, hereby decreasing yields and increasing returns. Columns 8 and 9 show that parameter estimates and significance levels remain similar when we perform a multivariate regression of residual stock-bond return comovements on all regressors simultaneously. The R^2's remain relatively low, however, with a maximum of about 7 percent.

The current results ignore interaction effects. If stock market illiquidity occurs at the same time as bond market illiquidity, the negative effect of shocks to equity illiquidity on residual stock-bond return comovements should be mitigated. In columns 10 and 11, we include the interaction between stock and bond illiquidity as an additional regressor. We confirm the negative relationship between $\hat{\varepsilon}_{s,t}\hat{\varepsilon}_{b,t}$ and shocks to equity market volatility and illiquidity. We find a positive and significant liquidity interaction effect, indicating that when liquidity drops in the equity *and* bond market, the stock illiquidity effect is reduced[13]. Note that the interaction term increases the R^2's from 7.08 percent to 11.58 percent, in case the zero return - zero volume equity illiquidity measure is used. In unreported results, we did not find significant effects from interacting bond and equity market illiquidity with equity market volatility, or from interacting shocks to consumer confidence with shocks to the other instruments.

8 Conclusions

The substantial time variation in stock-bond return correlations has long been viewed as puzzling. Without assessing what time variation in correlations a formal model of fundamentals can generate, this may be a premature judgment. For instance, much has been made of the negative correlation between bond and stock returns in recent times. However, the real economy and the inflation process have undergone some remarkable changes recently. In particular, it is well known that output and inflation volatility have decreased substantially since 1985. If bonds and stocks have similar exposures to these economic factors, their correlation should have decreased. It is also conceivable that these fundamental changes have affected risk aversion, a factor on which bonds and stocks may load with a different sign. While it remains difficult to think of economic factors that would cause a sudden and steep decrease of stock-bond return correlations into negative territory, it remains useful to quantify how much of the correlation dynamics can be attributed to fundamentals. This is what this paper sets out to do using a dynamic factor model with fundamental factors.

Importantly, we considered a large number of economic factors, and a large number of model specifications, some with scant structural restrictions. Yet, we fail to find a satisfactory fit with stock-bond return correlations. A number of our models have a satisfactory fit with the unconditional correlation between stocks and bonds. Specifications including risk aversion or economic uncertainty measures substantially outperform models that do not, suggesting that common variation in risk premiums is an essential component in any stock-bond return correlation model. We also find that the performance of our fundamental models improves when factor shocks are 'structurally' identified by means of a New-Keynesian model. Not unlike the pattern observed in the data, our fundamental-based models do generate positive correlations until the end of the 1980s, and decreasing and even negative correlations afterwards. Using fundamentals only, however, our models are unable to match both the timing and the magnitude of the correlation movements. In our last section, we examine some potential non-fundamental sources of these correlations. We find that the cross-residuals of our models load significantly on stock market uncertainty or volatility. While this may be a confirmation of the flight-to-quality phenomenon, it may also simply indicate that models that better explain the variability in the stock market may also help capture stock-bond return correlations. We also explored some liquidity factors. Liquidity factors are more and more viewed as being of primary importance in asset pricing. Although we model correlations at the quarterly frequency, stock market illiquidity seems to have important explanatory power for the part of bond and stock return correlations not explained by our fundamental models. We suspect that a model which combines high frequency liquidity factors with lower frequency fundamental factors may be more succesful at explaining stock and bond return correlation dynamics.

Notes

[1]Autocorrelation in daily stock and bond returns potentially biases our estimates of quarterly stock and bond return volatilities and correlations. While we do find a moderate degree of autocorrelation in both stock and bond returns, correcting for this bias (using 4 Newey and West (1987) lags) does not meaningfully alter stock-bond return volatilities and correlations.

[2]The expected output gap is measured as the median of individual forecasts of the output gap. We compute the individual output gap forecasts using individual real GDP growth forecasts from the survey of professional forecasters (see Data Appendix).

[3]Expected inflation is measured as the median of individual inflation forecasts from the survey of professional forecasters.

[4]In principle, the drift parameter μ and the feedback matrix A may also vary through time, especially if Γ_t and Σ_t depend on variables capturing structural changes. We investigate this possibility in Section 6.

[5]Allowing for two independent regime variables for the volatility of respectively the output gap and inflation leads to highly correlated ex ante probabilities.

[6]Adam and Padula (2003) advocate using survey forecasts instead of the rational expectations concept.

[7]In computing conditional correlations for the regime-switching models, we use ex-ante regime probabilities conditional on time $t-1$ information.

[8]We find mostly parameters in line with the extant literature, including a rather weak monetary transmission mechanism (see Bekaert, Cho, and Moreno (2006)).

[9]Note that we find idiosyncratic cash flow volatility to increase post 1986, yet the uncertainty regarding future cash flows, as measured by the Survey of Professional Forecasters, decreases in the 1990s.

[10]The Schwartz information criterion selects a VAR of order 1. Detailed estimation results are available on request.

[11]In unreported results, we confirm that this effect is mainly due to the part of stock volatility not explained by our fundamental factor model.

[12]The effect is only significant at the 10 percent level for the illiquidity measure which uses volume data.

[13]We obtain similar results when we condition the interaction effect also on a dummy that has the value of one when both the stock and bond illiquidity shocks are positive, and zero otherwise.

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Appendix

A Data Appendix

Our dataset consists of stock and bond returns and a number of economic (fundamental) and non-fundamental state variables for the US. Our sample period is from the fourth quarter of 1968 to the fourth quarter of 2004 for a total of 145 observations. The economic state variables are seasonally adjusted. Below we give details on the exact data sources used and on the way the series are constructed:

1. **Stock Excess Returns (r_s):** End-of-quarter NYSE/AMEX/NASDAQ value-weighted returns including dividends. The source is the Center for Research in Security Prices (CRSP) Stock File Indices. The returns are in excess of the US 3-month T-bill rate.

2. **Bond Excess Returns (r_b):** End-of-quarter 10-year bond returns. The source is the CRSP US Treasury and Inflation Module. The returns are in excess of the US 3-month T-bill rate.

3. **Inflation (π)**: Log difference in the Consumer Price Index for All Urban Consumers (All Items). The source is the Bureau of Labor Statistics.

4. **Expected Inflation (πe)**: Median survey reponse of expected growth in the GDP deflator over the next quarter. The source is the Survey of Professional Forecasters (SPF).

5. **Inflation Uncertainty (πd)**: Average SPF respondents' assessment of inflation uncertainty, taken from Bekaert and Engstrom (2006). The SPF survey contains information about the uncertainty in expected growth in the GDP deflator over the next year for each individual forecaster. Each respondent fills in probabilities on a histogram for values of expected growth in the GDP deflator over the next year. Based on these individual distributions, a measure of an individual's forecast uncertainty is constructed. Eventually, these individual measures are averaged out to create an aggregate measure for inflation uncertainty (see Bekaert and Engstrom (2006) for details). As a robustness measure for inflation uncertainty, we take the standard deviation of the SPF respondents' forecasts of expected growth in the GDP deflator over the next quarter.

6. **Output Gap (y):** The output measure is the real Gross Domestic Product. The source is the Bureau of Economic Analysis. The gap is computed as the output measure minus its quadratic trend.

7. **Expected Output Gap** (ye): Current output gap augmented with expected growth in output and the expected increase in potential growth. The latter is the deterministic increase in the quadratic trend. Expected growth in output is computed as the median survey reponse of expected growth in real GDP over the next quarter. The source is the Survey of Professional Forecasters (SPF).

8. **Output Uncertainty** (yd): Average SPF respondents' assessment of real output uncertainty, taken from Bekaert and Engstrom (2006). The SPF survey contains information about the uncertainty in expected real GDP growth over the next year for each individual forecaster. Each respondent fills in probabilities on a histogram for values of expected growth in real GDP over the next year. Based on these individual distributions, a measure of an individual's forecast uncertainty is constructed. Eventually, these individual measures are averaged out to create an aggregate measure for output uncertainty (see Bekaert and Engstrom (2006) for details). As a robustness measure for output uncertainty, we take the standard deviation of the SPF respondents' forecasts of expected growth in real GDP over the next quarter.

9. **Nominal Risk-free Rate** (i): 3-Month Treasury Bill: Secondary Market Rate. The source is the Federal Reserve.

10. **Cash Flow Growth (cg):** Dividend growth including repurchases, taken from Bekaert and Engstrom (2006). The source for the dividends is CRSP. The source for the repurchases is Securities Data Corporation. Dividend growth is transformed into cash flow growth using the ratio of repurchases to (seasonally adjusted) dividends.

11. **Cash Flow Uncertainty (cgd):** Standard deviation of the SPF respondents' forecasts of expected growth in corporate profits (after taxes) over the next quarter.

12. **Consumption Growth ($cons$):** Growth in real personal consumption expenditures. The source is US Department of Commerce: Bureau of Economic Analysis.

13. **Conditional Volatility of Consumption Growth ($consd$):** 60-month moving window of growth in real personal consumption expenditures (see figure below).

14. **Fundamental Risk Aversion (fra):** Our measure of fundamental risk aversion is based on the external habit specification of Campbell and Cochrane (1999), and taken from Bekaert and Engstrom (2006).

15. **Non-Fundamental Risk Aversion ($nfra$)**: The University of Michigan's Consumer Confidence Index (rescaled and orthogonalized on fundamental risk aversion)

16. **VIX Implied Volatility** (vix): Daily volatility index created by the Chicago Board Options Exchange. It measures the market's expectation of near term volatility as reflected in the options prices of S&P 500 stock index. The series starts in 1986.

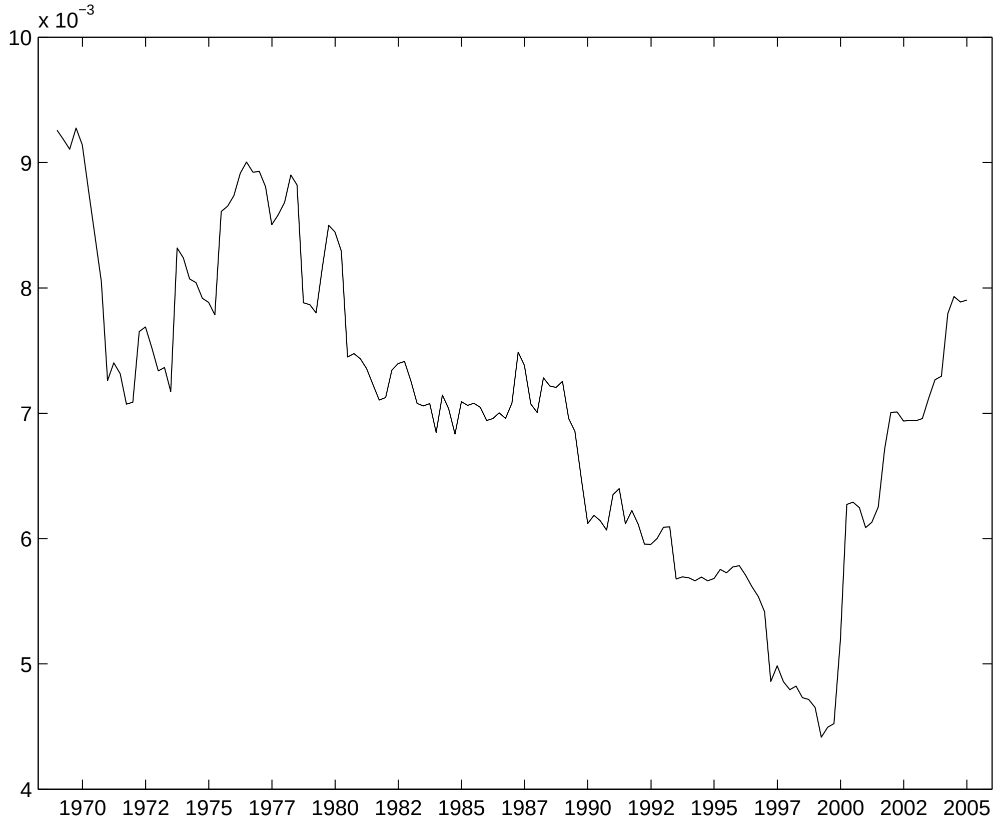
17. **Bond Market Illiquidity** ($illiq_b$): Monthly average of quoted bid-ask spreads across all maturities, taken from Goyenko (2006). He uses securities of 1 month, 3 months, 1, 2, 3, 5, 7, 10, 20, and 30 years to maturity, and deletes the first month of trading, when the security is 'on-the-run', as well as the last month of trading. Consequently, he calculates a monthly equally-weighted average of quoted spreads from daily observations for each security. Finally, the market-wide illiquidity measure is calculated as an equally-weighted average across all securities for each month.

18. **On/off the run spread**: Difference between the on-the-run 30-year government bond and a synthetically created bond with the same maturity and coupon schedules as the on-the-run bond, based on a yield curve fitted to off-the-run bond yields using the Svensson method.

19. **Equity Market Illiquidity** ($illiq_s$): Capitalization-based proportion of zero daily returns and/or zero volumes across all firms, aggegated over the quarter, obtained from Bekaert, Harvey, and Lundblad (2007).

The included figure shows the conditional volatility of consumption growth, as explained above:

Conditional Volatility of Consumption Growth



The included table shows some descriptive statistics and the unconditional correlations between the asset returns and state variables:

Summary Statistics

This table reports summary statistics and unconditional correlations for stock and bond returns and the different economic (fundamental) and non-fundamental state variables for the US. All data series are quarterly over the period 1968-2004. r_s is the stock return, r_b bond return, π inflation, πe expected inflation, πd inflation uncertainty, y output gap, ye expected output gap, yd output uncertainty, i nominal interest rate, cg cash flow growth, cgd cash flow uncertainty, $cons$ consumption growth, $consd$ consumption growth volatility, fra fundamental risk aversion, $nfra$ non-fundamental risk aversion, vix VIX implied volatility, $illiq_b$ bond market illiquidity and $illiq_s$ stock market illiquidity. The summary statistics are expressed in percentages.

	r_s	r_b	π	πe	πd	y	ye	yd	i	cg	cgd	$cons$	$consd$	fra	$nfra$	vix	$illiq_b$	$illiq_s$
1. Descriptive Stats																		
Mean	1.37	0.55	1.02	0.99	0.50	0.00	-0.09	1.47	1.52	0.60	2.92	0.82	0.70	3.78	0.00	21.27	17.14	9.79
Median	2.29	-0.25	0.80	0.85	0.44	-0.32	-0.26	1.39	1.42	0.60	2.60	0.86	0.71	3.63	-0.05	20.11	16.55	10.89
Max	22.90	13.66	3.04	2.29	0.93	4.34	4.83	2.29	3.76	38.93	6.86	2.30	0.93	5.40	1.13	44.57	39.28	16.71
Min	-26.43	-9.60	0.20	0.32	0.24	-6.66	-6.61	0.73	0.22	-22.36	1.17	-2.26	0.44	3.19	-0.72	11.46	2.88	0.73
Std	8.98	4.57	0.63	0.50	0.14	2.17	2.22	0.31	0.72	8.10	1.18	0.66	0.12	0.54	0.42	7.00	11.08	4.24
Skew	-0.42	0.50	1.03	0.95	1.05	-0.36	-0.37	0.90	0.75	0.56	0.82	-1.00	-0.16	1.52	0.58	1.11	0.13	-0.88
Kurt	3.49	3.04	3.47	3.00	3.53	3.26	3.32	3.48	3.97	6.65	3.15	6.23	2.49	4.51	2.85	4.35	1.57	2.75
2. Correlations																		
r_s	1.00	0.19	-0.17	-0.05	0.00	-0.09	-0.10	-0.01	-0.12	0.01	-0.04	0.34	-0.11	0.00	-0.13	-0.45	-0.11	0.02
r_b	0.19	1.00	-0.19	-0.13	-0.05	-0.23	-0.21	0.00	-0.22	0.25	0.00	0.26	-0.12	-0.03	0.07	0.21	-0.12	-0.02
π	-0.17	-0.19	1.00	0.84	0.55	0.06	0.01	0.44	0.57	-0.07	0.34	-0.31	0.65	0.55	0.42	-0.06	0.79	0.44
πe	-0.05	-0.13	0.84	1.00	0.76	-0.07	-0.14	0.50	0.76	-0.02	0.45	-0.25	0.53	0.72	0.33	-0.25	0.80	0.60
πd	0.00	-0.05	0.55	0.76	1.00	-0.16	-0.25	0.24	0.69	-0.01	0.53	-0.18	0.29	0.63	0.16	0.08	0.56	0.35
y	-0.09	-0.23	0.06	-0.07	-0.16	1.00	0.98	0.33	0.06	-0.07	-0.31	-0.04	-0.01	-0.50	0.02	0.29	-0.12	-0.02
ye	-0.10	-0.21	0.01	-0.14	-0.25	0.98	1.00	0.36	-0.02	-0.07	-0.36	0.05	0.01	-0.57	-0.04	0.27	-0.12	-0.01
yd	-0.01	0.00	0.44	0.50	0.24	0.33	0.36	1.00	0.32	-0.01	0.05	-0.02	0.45	0.10	0.22	0.07	0.45	0.46
i	-0.12	-0.22	0.57	0.76	0.69	0.06	-0.02	0.32	1.00	-0.09	0.40	-0.30	0.25	0.44	0.22	-0.09	0.64	0.54
cg	0.01	0.25	-0.07	-0.02	-0.01	-0.07	-0.07	-0.01	-0.09	1.00	-0.03	0.19	-0.01	0.02	-0.08	0.06	-0.06	-0.02
cgd	-0.04	0.00	0.34	0.45	0.53	-0.31	-0.36	0.05	0.40	-0.03	1.00	-0.23	0.30	0.44	0.29	-0.05	0.38	0.15
$cons$	0.34	0.26	-0.31	-0.25	-0.18	-0.04	0.05	-0.02	-0.30	0.19	-0.23	1.00	-0.10	-0.19	-0.30	0.07	-0.12	-0.02
$consd$	-0.11	-0.12	0.65	0.53	0.29	-0.01	0.01	0.45	0.25	-0.01	0.30	-0.10	1.00	0.24	0.37	-0.02	0.69	0.35
fra	0.00	-0.03	0.55	0.72	0.63	-0.50	-0.57	0.10	0.44	0.02	0.44	-0.19	0.24	1.00	0.00	-0.17	0.46	0.15
$nfra$	-0.13	0.07	0.42	0.33	0.16	0.02	-0.04	0.22	0.22	-0.08	0.29	-0.30	0.37	0.00	1.00	-0.01	0.43	0.36
vix	-0.45	0.21	-0.06	-0.25	0.08	0.29	0.27	0.07	-0.09	0.06	-0.05	0.07	-0.02	-0.17	-0.01	1.00	-0.15	-0.54
$illiq_b$	-0.11	-0.12	0.79	0.80	0.56	-0.12	-0.12	0.45	0.64	-0.06	0.38	-0.12	0.69	0.46	0.43	-0.15	1.00	0.60
$illiq_s$	0.02	-0.02	0.44	0.60	0.35	-0.02	-0.01	0.46	0.54	-0.02	0.15	-0.02	0.35	0.15	0.36	-0.54	0.60	1.00

B Overview of Regime-Switching Models

In Section 2, we compare the performance of four types of bivariate conditional variance-covariance models. The first three models, namely a bivariate asymmetric BEKK model, a regime-switching normal model, and a regime-switching ARCH model are well described in the literature (see e.g. Baele (2005)). The fourth model, which is to our knowledge new to the volatility literature and described below, makes the conditional stock-bond return variances (correlation) a function of a latent regime variable and the lagged quarterly ex-post variances (correlation). The latter are measured using daily stock-bond return data over the previous quarter.

Let $r_t = (r_{s,t}, r_{b,t})$ denote the vector of excess stock and bond returns, whose dynamics is decribed by the following set of equations:

$$
\begin{aligned}
r_t &= E_{t-1}\left[r_t\right] + \varepsilon_t \\
\varepsilon_t &\sim N\left(0, \Omega_t\right).
\end{aligned}
$$

The variance-covariance matrix Ω_t is specified as follows:

$$
\Omega_t = \begin{bmatrix} \sigma_{s,t}^2 & \sigma_{s,t}\sigma_{b,t}\rho_{s,b,t} \\ \sigma_{s,t}\sigma_{b,t}\rho_{s,b,t} & \sigma_{b,t}^2 \end{bmatrix}.
$$

The conditional stock and bond return variances $\sigma_{s,t}^2$ and $\sigma_{b,t}^2$ and the conditional stock-bond correlation $\rho_{s,b,t}$ are modeled as follows:

$$
\begin{aligned}
\sigma_{t,s}^2 &= \sigma_s^2(S_t) + \theta_s\left(S_t\right)\hat{\sigma}_{s,t-1}^2 \\
\sigma_{t,b}^2 &= \sigma_b^2(S_t) + \theta_b\left(S_t\right)\hat{\sigma}_{b,t-1}^2 \\
\rho_{s,b,t} &= \rho_{s,b}(S_t) + \theta_\rho\left(S_t\right)\hat{\rho}_{s,b,t-1}
\end{aligned}
$$

where $\hat{\sigma}_{s,t}^2$ and $\hat{\sigma}_{b,t}^2$ represent the time t realized stock and bond return variance, and $\hat{\rho}_{s,b,t}$ the ex-post stock-bond return correlation. To keep the regime-switching intercept in the correlation function within $[-1, 1]$, we parameterize it as $-1+2\exp\left(\alpha\left(S_t\right)\right)/\left(1+\exp\left(\alpha\left(S_t\right)\right)\right).$ We estimate models where the latent regime variable S_t can take on two and three states. All parameters are estimated using the maximum likelihood procedure developed by Hamilton (1989).

Table 1: Overview of the Different Statistical Correlation Models

This table gives an overview of the different conditional correlation models we estimate. The first three models are various versions of the bivariate BEKK model. Models 4 and 7 are regime-switching normal models with respectively 2 and 3 states. Models 5 and 8 augment these models incorporating GARCH and asymmetry effects. Models 6 and 9 extend further adding lagged realized correlation and realized volatilities to the specifications. The column 'States' shows how much different states are allowed in the specific model.

Model	**Description**	**States**
1	Diagonal BEKK bivariate GARCH model with Asymmetry	1
2	Full BEKK bivariate GARCH model with Asymmetry	1
3	Diagonal BEKK bivariate model with Asymmetry and Regime-Switches	1
4	Markov Switching Normal Volatility Model	2
5	Markov Switching GARCH Volatility Model with Asymmetry	2
6	Markov Switching Volatility Model with Realized Correlation/Volatility	2
7	Markov Switching Normal Volatility Model	3
8	Markov Switching GARCH Volatility Model with Asymmetry	3
9	Markov Switching Volatility Model with Realized Correlation/Volatility	3

Table 2: Specification Test Results for the Statistical Correlation Models

This table reports the results of the specification tests for the different models. Panel A reports covariance specification tests as well as two heuristic statistics. The specification tests are conducted on the difference between the model-implied covariances and the product of stock and bond residuals. We test for zero mean and serial correlation of respectively order 2 and 4. The joint test combines the zero mean test and the test for fourth-order serial correlation. P-values are reported between brackets. The heuristic test computes the mean absolute difference between the model-implied and the quarterly ex post correlation, one period ahead. The R^2 test computes the R^2 from a regression of the ex post correlation on the model-implied correlation. Panel B reports the Akaike, Schwarz, and Hannan-Quinn information criteria. The lower the criteria, the better the model fits the data.

Panel A: Covariance Specification Tests

	Mean	**Ser. Corr**		**Joint**	**Heuristic Test**	**R^2 Test**
Model		**2 lags**	**4 lags**			
1	0.025	5.327	8.277	8.679	0.243	0.140
	(0.874)	*(0.255)*	*(0.082)*	*(0.123)*		
2	0.002	0.189	2.777	3.046	0.262	0.065
	(0.967)	*(0.996)*	*(0.596)*	*(0.693)*		
3	0.058	6.035	9.709	9.879	0.290	0.156
	(0.810)	*(0.197)*	*(0.046)*	*(0.079)*		
4	0.000	6.206	9.641	9.649	0.228	0.252
	(0.997)	*(0.184)*	*(0.047)*	*(0.086)*		
5	0.512	8.193	12.534	12.819	0.256	0.225
	(0.474)	*(0.085)*	*(0.014)*	*(0.025)*		
6	0.406	5.863	8.796	9.770	0.242	0.362
	(0.524)	*(0.210)*	*(0.066)*	*(0.082)*		
7	0.007	7.248	11.014	11.368	0.238	0.320
	(0.931)	*(0.123)*	*(0.026)*	*(0.045)*		
8	0.087	8.381	13.550	15.419	0.270	0.187
	(0.768)	*(0.079)*	*(0.009)*	*(0.009)*		
9	1.913	4.278	5.745	7.440	0.268	0.394
	(0.167)	*(0.370)*	*(0.219)*	*(0.190)*		

Panel B: Information Criteria

Model	**Nr. Par.**	**Akaike**	**Schwarz**	**Hannan-Quinn**
1	11	-5.401	-5.174	-5.431
2	17	-5.400	-5.050	-5.447
3	16	-5.485	-5.155	-5.529
4	10	-5.394	-5.188	-5.421
5	16	-5.462	-5.132	-5.506
6	16	**-5.555**	**-5.225**	**-5.599**
7	17	-5.397	-5.047	-5.444
8	23	-5.508	-5.034	-5.572
9	26	-5.502	-4.966	-5.573

Table 3: Estimation Results for Two State Markov Switching Volatility Model with Realized Correlation and Volatility

This table reports the estimation results for the two state Markov switching volatility model with the realized correlation and variances as additional instruments. The conditional correlation and variances are a function of a constant and respectively the past realized correlation and the past realized variance. Both parameters are allowed to switch according to a two state regime variable. Realized stock-bond return correlation is computed as the sum of the cross-product of daily within-quarter stock and bond returns. Realized stock (bond) variance is computed as the sum of squared daily within quarter stock (bond) returns. P-values are reported between brackets.

	Volatility Stock		**Volatility Bonds**		**Correlation**		**Prob**
	constant	*ex-post*	*constant*	*ex-post*	*constant*	*ex-post*	
Regime 1	0.000	1.893	0.029	1.153	0.363	0.591	0.981
	(0.394)	*(0.000)*	*(0.001)*	*(0.064)*	*(0.004)*	*(0.023)*	*(0.000)*
Regime 2	0.108	0.009	0.039	0.018	-0.601	0.004	0.951
	(0.000)	*(0.398)*	*(0.000)*	*(0.398)*	*(0.000)*	*(0.398)*	*(0.000)*

Table 4: Model Selection Tests

This table presents the model selection tests for respectively the three factor models (Panel A), the four factor models (Panel B) and the eight factor models (Panel C), as explained in Section 4.2. The factors are identified using the state variable models explained in Section 3.2. For each of these models, we differentiate between eight specifications depending on the beta specification (constant or time-varying) and the volatility specification (homoskedastic, state-dependent, regime-switching or regime-switching state-dependent). The specification tests are conducted on the cross-product of the stock and bond residuals, using the generalized method of moments. We have a zero-mean test, i.e. Mean(0). SC(2) and SC(4) test for respectively second-order and fourth-order serial correlation. P-values are given in brackets. The distance measures compute the mean absolute deviation of the model-implied correlation from respectively our proxy for the actual conditional correlation as obtained in Section 2 (column 4) and the realized correlation as obtained using the daily data (column 5). Column 6 reports the Regime Classification Measure (RCM) obtained from evaluating the best fitting empirical model of Section 2 on the stock and bond residuals of the factor model. The higher the regime classification measure, the better the specific model performs. The RCM statistic of the model applied to the original data is 12.4. Finally, we present the unadjusted and the adjusted R^2 of the factor model for respectively stock and bond returns.

Panel A: Three Factor Models

	Specification Tests			**Distance $\rho_{s,b,t}$**		**RCM**	**R^2 ($r_{s,t}$ / $r_{b,t}$)**	
Volatility	**Mean(0)**	**SC(2)**	**SC(4)**	**Actual ρ**	**Realized ρ**		**Unadj.**	**Adj.**
Constant Beta Specification								
Homoskedastic	3.279	5.298	6.137	0.450	0.318	14.992	0.078	0.058
	(0.070)	*(0.258)*	*(0.189)*				0.258	0.242
State-Dependent	3.295	4.902	5.532	0.448	0.317	15.311	0.079	0.059
	(0.069)	*(0.297)*	*(0.237)*				0.272	0.256
Regime-Switching	2.758	4.873	5.970	0.451	0.318	14.899	0.056	0.036
	(0.097)	*(0.301)*	*(0.201)*				0.233	0.217
RS State-Dependent	2.892	4.935	5.701	0.458	0.327	14.989	0.080	0.060
	(0.089)	*(0.294)*	*(0.223)*				0.231	0.215
Dynamic Beta Specification								
Homoskedastic	3.447	4.864	5.063	0.454	0.332	15.124	0.106	0.087
	(0.063)	*(0.302)*	*(0.281)*				0.270	0.254
State-Dependent	3.516	4.266	4.605	0.451	0.320	15.804	0.108	0.088
	(0.061)	*(0.371)*	*(0.330)*				0.287	0.272
Regime-Switching	2.947	4.422	4.511	0.445	0.313	15.849	0.068	0.048
	(0.086)	*(0.352)*	*(0.341)*				0.256	0.240
RS State-Dependent	3.090	4.217	4.553	0.457	0.325	15.844	0.096	0.077
	(0.079)	*(0.377)*	*(0.336)*				0.254	0.238

Panel B: Four Factor Models

	Specification Tests			Distance $\rho_{s,b,t}$		RCM	R^2 ($r_{s,t}$ / $r_{b,t}$)	
Volatility	**Mean(0)**	**SC(2)**	**SC(4)**	**Actual ρ**	**Realized ρ**		**Unadj.**	**Adj.**
Constant Beta Specification								
Homoskedastic	3.425	5.705	7.476	0.452	0.320	14.368	0.057	0.030
	(0.064)	*(0.222)*	*(0.113)*				0.271	0.250
State-Dependent	3.236	5.083	7.359	0.421	0.297	13.990	0.076	0.049
	(0.072)	*(0.279)*	*(0.118)*				0.285	0.265
Regime-Switching	3.157	4.552	7.754	0.424	0.297	14.782	0.087	0.061
	(0.076)	*(0.336)*	*(0.101)*				0.269	0.248
RS State-Dependent	3.666	6.259	10.612	0.430	0.306	15.621	0.076	0.049
	(0.056)	*(0.181)*	*(0.031)*				0.272	0.251
Dynamic Beta Specification								
Homoskedastic	3.004	3.881	4.534	0.452	0.334	14.905	0.106	0.080
	(0.083)	*(0.422)*	*(0.339)*				0.298	0.278
State-Dependent	3.088	2.848	4.105	0.415	0.312	14.844	0.125	0.099
	(0.079)	*(0.584)*	*(0.392)*				0.315	0.295
Regime-Switching	2.982	4.119	6.018	0.408	0.295	13.823	0.127	0.102
	(0.084)	*(0.390)*	*(0.198)*				0.298	0.278
RS State-Dependent	3.139	5.947	8.243	0.415	0.321	14.392	0.134	0.109
	(0.076)	*(0.203)*	*(0.083)*				0.306	0.286

Panel C: Eight Factor Models

	Specification Tests			Distance $\rho_{s,b,t}$		RCM	$\mathbf{R}^2$ ($r_{s,t}$ / $r_{b,t}$)	
Volatility	**Mean(0)**	**SC(2)**	**SC(4)**	**Actual** ρ	**Realized** ρ		**Unadj.**	**Adj.**
Constant Beta Specification								
Homoskedastic	2.093	4.677	4.726	0.424	0.291	18.361	0.082	0.028
	(0.148)	*(0.322)*	*(0.317)*				0.357	0.319
State-Dependent	2.676	3.612	4.265	0.424	0.293	17.531	0.071	0.016
	(0.102)	*(0.461)*	*(0.371)*				0.348	0.310
Regime-Switching	3.063	4.091	4.548	0.428	0.300	18.167	0.077	0.022
	(0.080)	*(0.394)*	*(0.337)*				0.326	0.286
RS State-Dependent	3.398	3.578	4.317	0.431	0.305	17.921	0.080	0.025
	(0.065)	*(0.466)*	*(0.365)*				0.331	0.291
Dynamic Beta Specification								
Homoskedastic	1.841	3.750	4.462	0.409	0.279	21.758	0.170	0.121
	(0.175)	*(0.441)*	*(0.347)*				0.396	0.360
State-Dependent	2.482	3.352	4.860	0.406	0.280	24.250	0.168	0.119
	(0.115)	*(0.501)*	*(0.302)*				0.387	0.351
Regime-Switching	2.708	4.419	5.773	0.395	0.274	23.913	0.168	0.119
	(0.100)	*(0.352)*	*(0.217)*				0.353	0.315
RS State-Dependent	2.998	4.012	5.635	0.401	0.282	24.296	0.174	0.125
	(0.083)	*(0.404)*	*(0.228)*				0.364	0.326

Table 5: Estimation Results for the Factor Models

This table reports the estimation results for respectively the selected three, four and eight factor models. Each model comprises the specification with time-varying betas and regime-switching volatilities. The dynamic betas for the factor models are specificied as explained in Section 3.1.3. The (expected) output gap and output uncertainty exposures are a function of the lagged output uncertainty. The (expected) inflation and inflation uncertainty exposures are a function of the lagged inflation uncertainty. The short rate exposure for stocks (bonds) is a function of the lagged (log) payout ratio (the lagged short rate). The short rate is expressed in percentages. The risk aversion exposure is a function of the (lagged) risk aversion itself. Finally, the cash flow growth exposure is a function of lagged cash flow growth uncertainty. The instruments in the beta specifications are standardized to improve the readability of the table. The estimated betas are shown with p-values between brackets, computed using White heteroskedasticity-consistent standard errors.

	Stocks						**Bonds**					
Factor	**3 Factor**		**4 Factor**		**8 Factor**		**3 Factor**		**4 Factor**		**8 Factor**	
	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
c	0.014		0.016		0.019		0.006		0.010		0.010	
	(0.070)		*(0.036)*		*(0.006)*		*(0.052)*		*(0.007)*		*(0.002)*	
F^y	5.898	-0.912	2.232	-0.088	2.216	-0.034	-0.291	-0.253	-0.134	-0.329	-0.300	-0.288
	(0.015)	*(0.639)*	*(0.039)*	*(0.908)*	*(0.033)*	*(0.968)*	*(0.796)*	*(0.776)*	*(0.756)*	*(0.116)*	*(0.543)*	*(0.236)*
F^π	-3.748	-2.588	-2.476	-2.373	-0.950	-1.200	-0.725	-0.350	0.347	-0.436	0.386	0.193
	(0.177)	*(0.354)*	*(0.300)*	*(0.331)*	*(0.701)*	*(0.620)*	*(0.516)*	*(0.705)*	*(0.724)*	*(0.636)*	*(0.749)*	*(0.863)*
F^{ye}					-4.579	3.488					-1.251	-0.123
					(0.102)	*(0.179)*					*(0.409)*	*(0.911)*
F^{yd}					7.627	0.940					4.742	-0.484
					(0.133)	*(0.836)*					*(0.056)*	*(0.773)*
$F^{\pi e}$					8.350	-20.730					1.650	-4.898
					(0.408)	*(0.002)*					*(0.672)*	*(0.186)*
$F^{\pi d}$					-28.046	13.568					-4.184	0.916
					(0.040)	*(0.382)*					*(0.479)*	*(0.902)*
F^i	0.069	-2.090	2.842	-7.139	1.338	-4.029	-13.077	2.603	-11.874	0.758	-12.974	1.844
	(0.990)	*(0.664)*	*(0.538)*	*(0.078)*	*(0.809)*	*(0.425)*	*(0.000)*	*(0.059)*	*(0.000)*	*(0.604)*	*(0.000)*	*(0.176)*
F^{fra}			-8.719	-5.385					-1.988	-4.162		
			(0.162)	*(0.351)*					*(0.486)*	*(0.130)*		
F^{cg}					0.013	0.201					0.147	0.054
					(0.933)	*(0.119)*					*(0.000)*	*(0.175)*

Table 6: Model Selection Tests for Models with Different Proxies for Output and Uncertainty

This table reports the results for the model selection tests of the optimal three, four and eight factor models for different proxies for our state variables. Models (1)-(4) estimate three factor models with different proxies for output. Model (1) uses the Hodrick Prescott filtered value of output. Model (2) uses the measure provided by the CBO. Model (3) uses GDP growth. Model (4) uses consumption growth for non-durables. Models (5) and (6) use respectively GDP and consumption growth in our four factor model. Models (7) and (8) use respectively GDP and consumption growth in our eight factor model. Models (9) and (10) estimate eight factor models with different proxies for output and inflation uncertainty. Model (9) uses the standard deviation of the real GDP growth (inflation) forecasts of individual professional forecasters. Model (10) uses the conditional volatility of consumption growth, calculated as the 60-month moving window volatility of real consumption growth for non-durables. The results for the original models are provided as a benchmark.

			Specification Tests			**Distance $\rho_{s,b,t}$**		**RCM**	**R^2 ($r_{s,t}$ / $r_{b,t}$)**	
Model	**Factors**	**Variable**	**Mean(0)**	**SC(2)**	**SC(4)**	**Actual ρ**	**Realized ρ**		**Unadj.**	**Adj.**
	3	**Benchmark**	2.947	4.422	4.511	0.445	0.313	15.849	0.068	0.048
			(0.086)	*(0.352)*	*(0.341)*				0.256	0.240
(1)	**3**	**Gap (HP)**	3.418	5.017	5.248	0.460	0.330	15.753	0.056	0.036
			(0.064)	*(0.286)*	*(0.263)*				0.256	0.240
(2)	**3**	**Gap (CBO)**	3.107	4.886	4.953	0.446	0.315	16.114	0.066	0.046
			(0.078)	*(0.299)*	*(0.292)*				0.250	0.234
(3)	**3**	**GDP Growth**	3.399	3.726	4.339	0.432	0.304	18.693	0.133	0.114
			(0.065)	*(0.444)*	*(0.362)*				0.334	0.320
(4)	**3**	**Cons. Growth**	2.131	2.936	4.240	0.410	0.286	21.699	0.194	0.177
			(0.144)	*(0.569)*	*(0.375)*				0.351	0.337
	4	**Benchmark**	2.982	4.119	6.018	0.408	0.295	13.823	0.127	0.102
			(0.084)	*(0.390)*	*(0.198)*				0.298	0.278
(5)	**4**	**GDP Growth**	2.291	3.696	9.962	0.418	0.298	15.108	0.112	0.087
			(0.130)	*(0.449)*	*(0.041)*				0.327	0.308
(6)	**4**	**Cons. Growth**	1.586	3.105	5.870	0.414	0.298	18.919	0.142	0.117
			(0.208)	*(0.540)*	*(0.209)*				0.339	0.320
	8	**Benchmark**	2.708	4.419	5.773	0.395	0.274	23.913	0.168	0.119
			(0.100)	*(0.352)*	*(0.217)*				0.353	0.315
(7)	**8**	**GDP Growth**	2.265	2.741	4.097	0.409	0.286	23.065	0.162	0.112
			(0.132)	*(0.602)*	*(0.393)*				0.367	0.330
(8)	**8**	**Cons. Growth**	1.602	3.301	5.056	0.408	0.283	25.630	0.184	0.135
			(0.206)	*(0.509)*	*(0.282)*				0.351	0.313
(9)	**8**	**Dispersion**	3.890	2.803	2.918	0.402	0.290	26.249	0.178	0.129
			(0.049)	*(0.591)*	*(0.572)*				0.420	0.386
(10)	**8**	**Cons. Vol.**	2.005	1.991	4.351	0.420	0.293	22.398	0.201	0.154
			(0.157)	*(0.737)*	*(0.361)*				0.343	0.304

Table 7: Estimation Results for Different Expected Return Specifications of Three Factor Model

This table reports model selection tests (Panel A) and parameter estimates (Panel B) for different expected return specifications for the three factor model. We differentiate between 5 specifications: the specification with constant expected returns (*Const*), which is the benchmark model; the specification in which the expected returns are a linear function of instruments as the lagged log earnings yield ey_{t-1}, the lagged nominal interest rate i_{t-1} and the lagged term spread $term_{t-1}$ (*Instr*); three specifications in which the expected returns are a linear function of respectively the high exogenous volatility regime variable (s_t^{ex}), the high interest rate volatility regime variable (s_t^{ir}), and the active monetary policy regime variable (s_t^{m}), as identified in the selected structural three state variable model. The regime variables take on a value of one when the the ex-ante probabilities are larger than 0.5, and zero otherwise. Panel B reports the parameter estimates for the different expected return specifications with p-values between brackets, computed using White heteroskedasticity-consistent standard errors.

Panel A: Model Selection Tests

	Specification Tests			**Distance $\rho_{s,b,t}$**		**RCM**	**R^2 ($r_{s,t}$ / $r_{b,t}$)**	
$E_{t-1}(r_t)$	**Mean(0)**	**SC(2)**	**SC(4)**	**Actual ρ**	**Realized ρ**		**Unadj.**	**Adj.**
Const.	2.947	4.422	4.511	0.445	0.313	15.849	0.068	0.048
	(0.086)	*(0.352)*	*(0.341)*				0.256	0.240
Instr.	2.039	4.250	4.630	0.417	0.290	18.492	0.108	0.089
	(0.153)	*(0.373)*	*(0.327)*				0.323	0.309
s_t^{ex}	2.920	4.615	4.712	0.446	0.314	16.098	0.076	0.056
	(0.087)	*(0.329)*	*(0.318)*				0.263	0.247
s_t^{ir}	3.003	4.611	4.836	0.449	0.317	16.095	0.077	0.057
	(0.083)	*(0.330)*	*(0.304)*				0.261	0.245
s_t^{m}	2.917	4.346	4.503	0.446	0.314	15.865	0.076	0.057
	(0.088)	*(0.361)*	*(0.342)*				0.258	0.242

Panel B: Expected Return Specifications

	c	ey_{t-1}	i_{t-1}	$term_{t-1}$	c	s_t^{ex}	c	s_t^{ir}	c	s_t^{m}
$E_{t-1}(r_{s,t})$	0.286	0.057	-3.375	4.402	0.015	-0.003	0.016	-0.017	0.012	0.007
	(0.051)	*(0.054)*	*(0.086)*	*(0.194)*	*(0.108)*	*(0.863)*	*(0.054)*	*(0.660)*	*(0.307)*	*(0.761)*
$E_{t-1}(r_{b,t})$	-0.043	-0.003	1.487	5.678	0.009	-0.008	0.005	0.016	0.005	0.006
	(0.305)	*(0.383)*	*(0.083)*	*(0.001)*	*(0.023)*	*(0.312)*	*(0.143)*	*(0.578)*	*(0.344)*	*(0.594)*

Table 8: Model Selection Tests for Different Beta Specifications of Eight Factor Model

This table reports the model selection tests for alternative beta specifications of the the eight factor model. The first two specifications are respectively the constant beta and the dynamic beta specification as explained in Section 3.1.3. In the next three cases, the betas of each factor are respectively a function of the high exogenous volatility regime variable (s_t^{ex}), the high interest rate volatility regime variable (s_t^{ir}), and the high cash flow growth volatility regime variable (s_t^{m}), as identified in the selected eight factor model. In the last four cases, the betas of each factor are respectively a function of the NBER recession dummy, a Volcker dummy for the period 1979-1982, a post-Volcker dummy for the period after 1982, and a dummy for the break in output volatility in 1984.

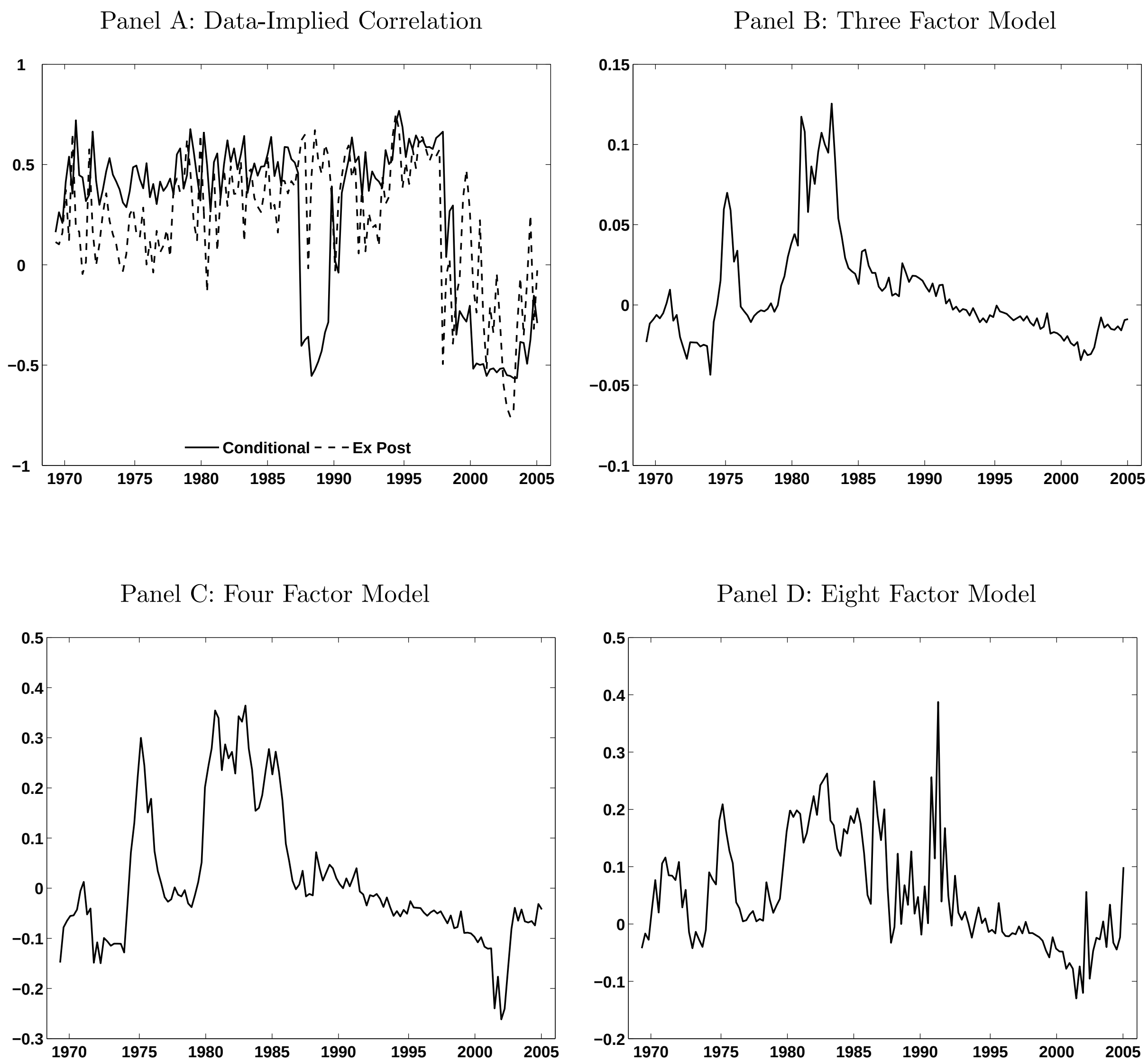
	Specification Tests			**Distance $\rho_{s,b,t}$**		**RCM**	**R^2 ($r_{s,t}$ / $r_{b,t}$)**	
Beta Specification	**Mean(0)**	**SC(2)**	**SC(4)**	**Actual ρ**	**Realized ρ**		**Unadj.**	**Adj.**
Constant	3.063	4.091	4.548	0.428	0.300	18.167	0.077	0.022
	(0.080)	*(0.394)*	*(0.337)*				0.326	0.286
Original	2.708	4.419	5.773	0.395	0.274	23.913	0.168	0.119
	(0.100)	*(0.352)*	*(0.217)*				0.353	0.315
s_t^{ex}	2.743	3.018	3.531	0.388	0.319	20.079	0.231	0.186
	(0.098)	*(0.555)*	*(0.473)*				0.346	0.308
s_t^{ir}	1.704	2.471	2.921	0.384	0.290	21.690	0.171	0.122
	(0.192)	*(0.650)*	*(0.571)*				0.456	0.424
s_t^{m}	1.503	3.626	4.236	0.322	0.304	30.868	0.236	0.190
	(0.220)	*(0.459)*	*(0.375)*				0.415	0.380
NBER Recession Dummy	1.429	6.060	7.065	0.437	0.360	21.191	0.263	0.219
	(0.232)	*(0.195)*	*(0.132)*				0.398	0.362
Volcker Dummy 79-82	2.389	3.258	3.463	0.411	0.301	18.841	0.161	0.111
	(0.122)	*(0.516)*	*(0.483)*				0.439	0.406
Post-Volcker Dummy 82	1.658	3.489	4.598	0.363	0.354	26.922	0.273	0.230
	(0.198)	*(0.480)*	*(0.331)*				0.379	0.342
Break Output Volatility 84	1.927	2.050	2.685	0.345	0.342	33.691	0.277	0.235
	(0.165)	*(0.727)*	*(0.612)*				0.395	0.359

Table 9: Estimation Results for the Residual Regressions

This table reports estimation results from a regression of the cross-product of the residuals from our preferred fundamental model on the VIX implied volatility index, the 30-year bond on/off the run spread, and on innovations in conditional equity market volatility (estimated in Section 2), the University of Michigan's Consumer Confidence Index, the bond illiquidity measures from Goyenko (2006), the zero return and zero return / volume equity market illiquidity measure of Bekaert, Harvey, and Lundblad (2007), as well as the interaction between bond and equity market illiquidty. Except for the interaction effect, all parameter estimates are multiplied by 100. Innovations are calculated using a VAR of order 1. P-values based on White (1980) standard errors are between brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	0.59	2.207	0.591	2.309	0.591	0.591	0.591	0.591	0.591	0.418	0.591
	(0.028)	(0.025)	(0.028)	(0.078)	(0.028)	(0.026)	(0.024)	(0.021)	(0.022)	(0.078)	(0.020)
Equity Volatility	-157.2							-183.8	-130.6	-200.9	-127.7
	(0.014)							(0.005)	(0.056)	(0.003)	(0.049)
VIX		-0.111									
		(0.036)									
Consumer Confidence			0.029					0.045	0.053	0.037	0.041
			(0.403)					(0.227)	(0.148)	(0.318)	(0.259)
On/Off-the-Run Spread				-0.138							
				(0.037)							
Bond Illiquidity					18.9			22.8	14.2	14.2	33.8
					(0.404)			(0.279)	(0.500)	(0.501)	(0.090
Equity Illiquidity						-1454.5		-1764.9		-1876.8	
(zero return/volume)						(0.173)		(0.087)		(0.060)	
Equity Illiquidity							-61.9		-63.4		-65.4
(zero return)							(0.079)		(0.069)		(0.055)
Interaction Bond/Equity Illiquidity										129.45	34.79
(zero return)										(0.029)	(0.027)
Adjusted R2	3.47%	6.73%	-0.17%	7.89%	0.00%	2.49%	4.49%	7.08%	5.74%	11.58%	8.84%

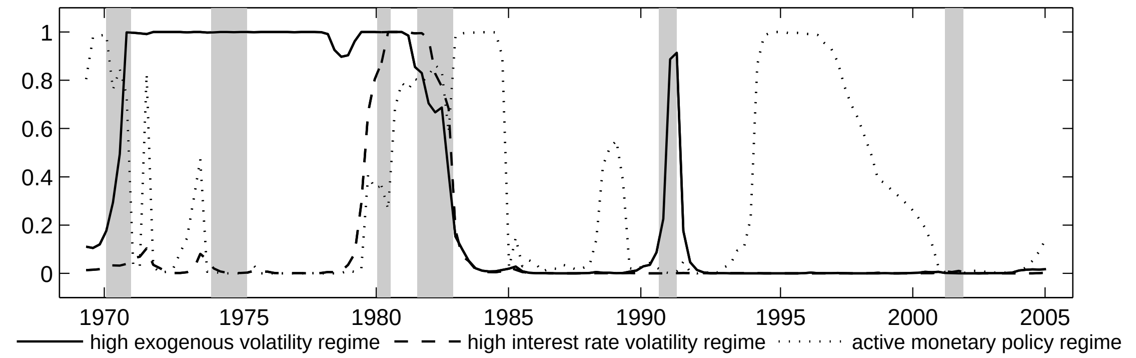
Figure 1: Data-Implied and Model-Implied Conditional Correlations



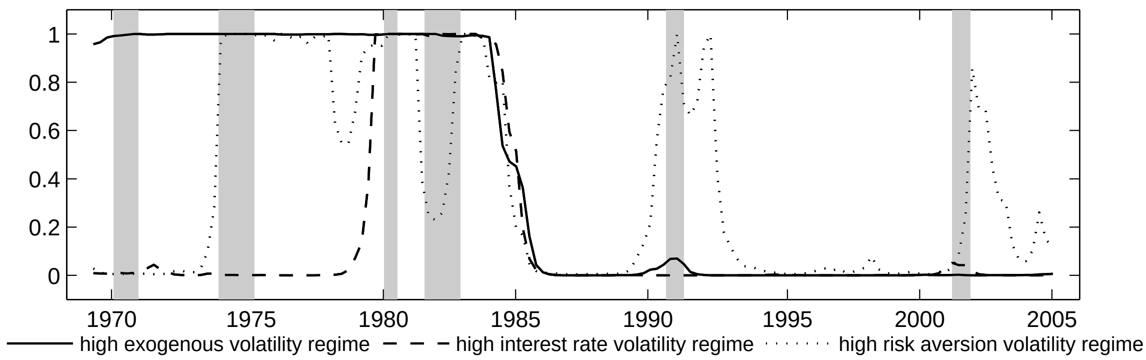
This figure plots the data-implied correlations (Panel A) and the model-implied correlations for respectively the best performing three factor model (Panel B), four factor model (Panel C) and eight factor model (Panel D). Model-implied correlations are computed as shown in Section 3.1.1. For the data-implied correlations, we differentiate between the *conditional* correlation based on the two state markov switching volatility model with realized correlation and volatilities as extra instruments, and the quarterly *ex post* correlation.

Figure 2: Smoothed Probabilities of Regimes in Different State Variable Models

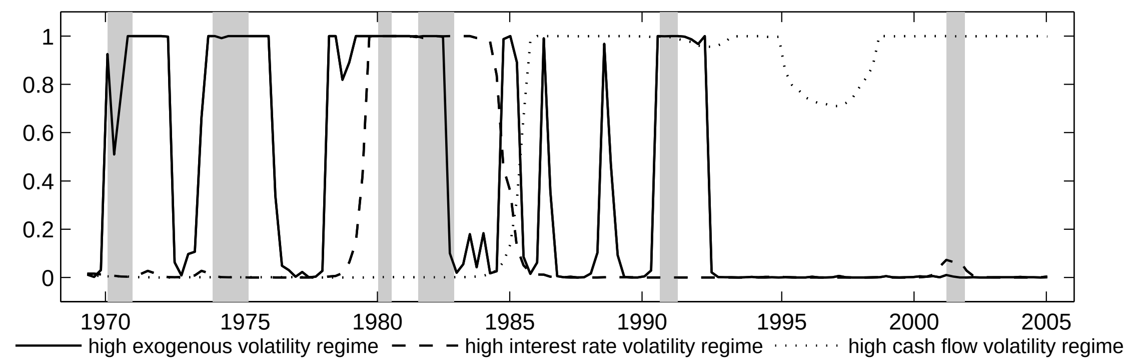
Panel A: Three State Variable Model



Panel B: Four State Variable Model



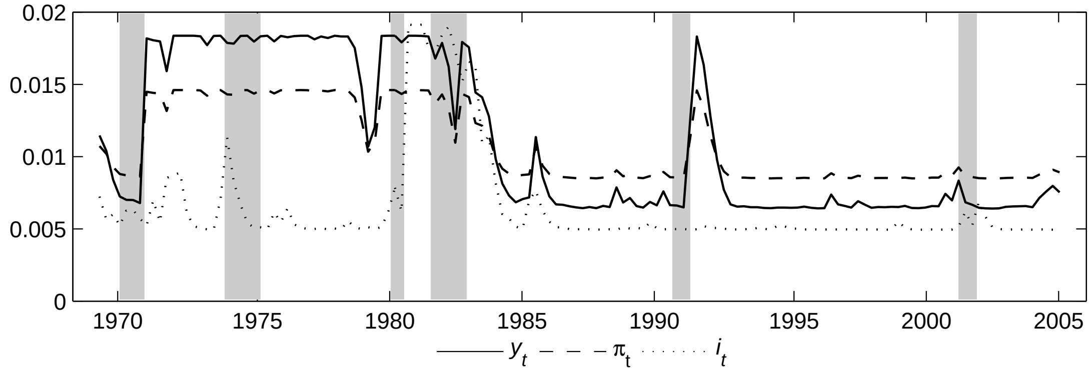
Panel C: Eight State Variable Model



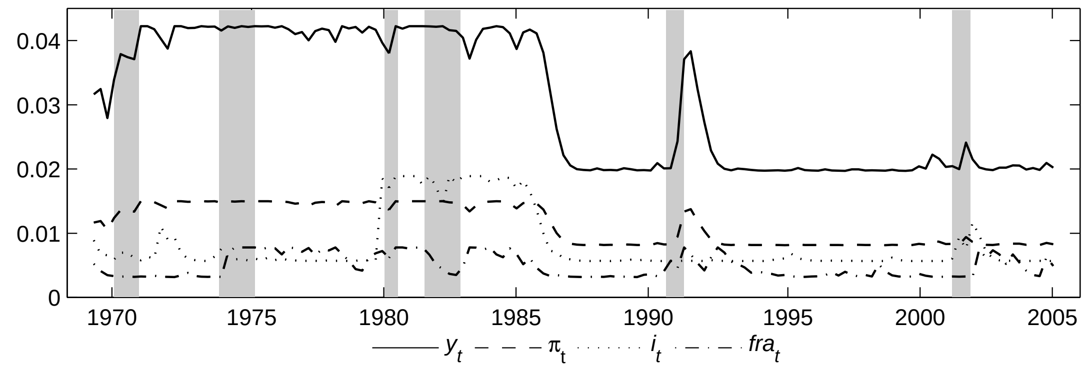
This figure shows the smoothed probabilities of the three independent regimes in respectively the selected structural three state variable model (Panel A), the selected non-structural four state variable model (Panel B), and the selected non-structural eight state variable model (Panel C). The different regimes are defined in Section 3.2. All three panels show the smoothed probability of a high exogenous volatility regime (i.e. high output gap and inflation shock volatility) and the smoothed probability of a high interest rate shock volatility. Panel A further shows the smoothed probability of an active monetary policy regime in which the FED aggressively stabilizes the price level; Panel B the smoothed probability of a high risk aversion shock volatility regime; Panel C the smoothed probability of a high cash flow growth shock volatility regime. NBER recessions are shaded gray.

Figure 3: Volatility of the Factors in Different State Variable Models

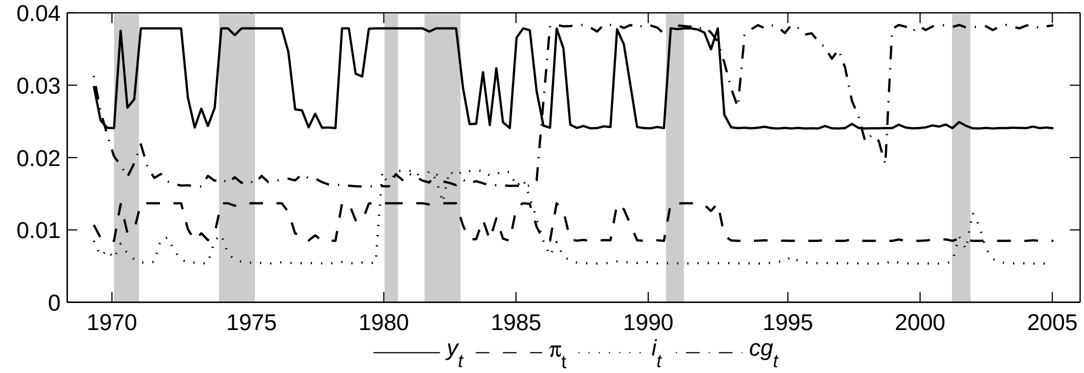
Panel A: Three State Variable Model



Panel B: Four State Variable Model

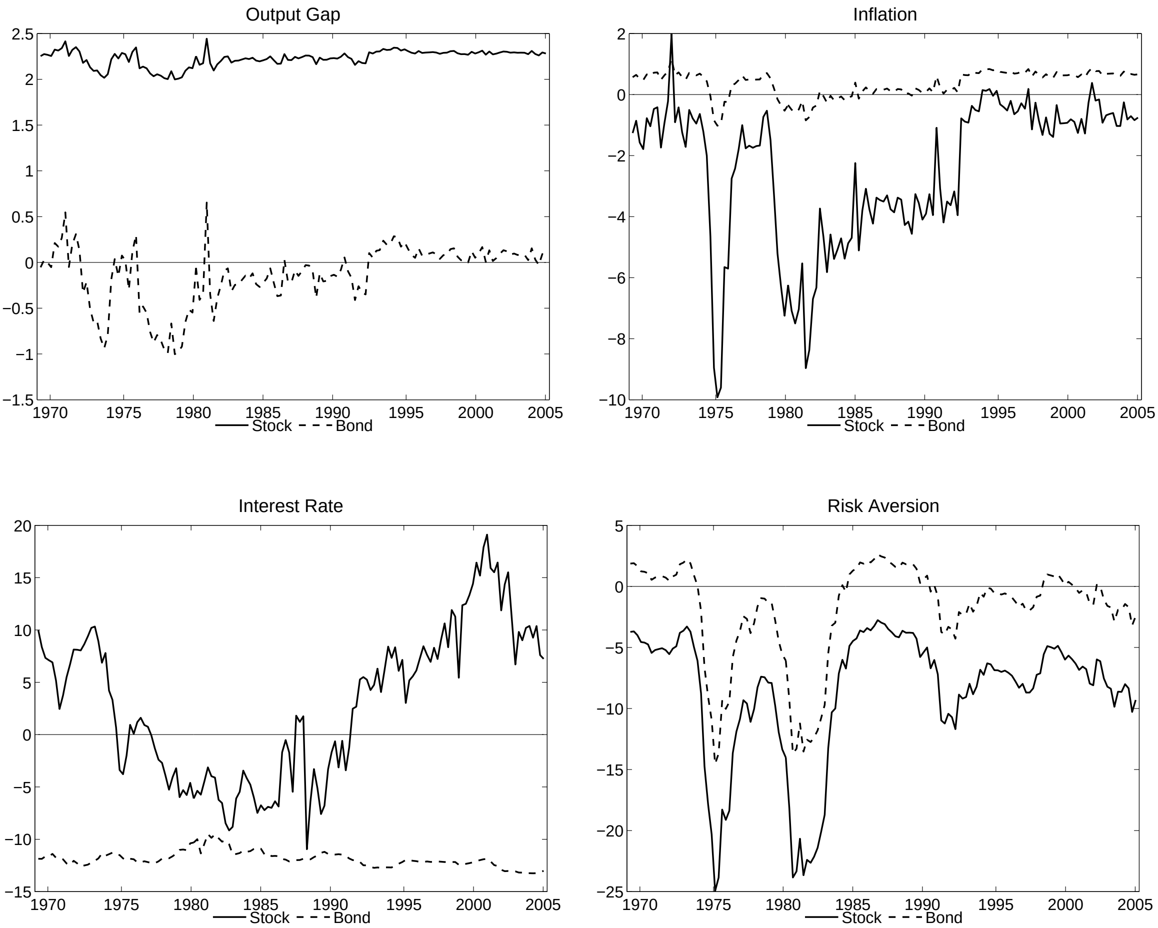


Panel C: Eight State Variable Model



This figure shows the conditional volatilities (annualized) of the various factors identified in respectively the selected structural three state variable model (Panel A), the selected non-structural four state variable model (Panel B), and the selected non-structural eight state variable model (Panel C). For each model, the factor volatilities are identified according to the regime-switching volatility specification. y_t refers to the output gap factor; π_t the inflation factor; i_t the interest rate factor; fra_t the risk aversion factor; cg_t the cash flow growth factor. Cash flow growth factor volatility is divided by 10 as to make it comparable with the other factor volatilities. NBER recessions are shaded gray.

Figure 4: Factor Exposures in the Four Factor Model



This plot shows the dynamic factor exposures for the ouput gap, inflation, interest rate and risk aversion shocks for the selected four factor model. The factor model comprises the specification with time-varying betas and regime-switching volatilities. The dynamic betas for the factor models are specificied as explained in Section 3.1.3. The output gap exposure is a function of the lagged output uncertainty. The inflation exposure is a function of the lagged inflation uncertainty. Both output and inflation uncertainty fluctuate between 0.1 and 1.2. The short rate exposure for stocks (bond) is a function of the lagged (log) payout ratio (the lagged short rate). The short rate is expressed in percentages. The risk aversion exposure is a function of the (lagged) risk aversion itself. The instruments in the beta specifications are standardized.