Gone with the Vol: A Decline in Asset Return Predictability during the Great Moderation
ONLINE APPENDIX

Alex Hsu[*], Francisco Palomino[†], and Liang Qian[‡]

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[*]Georgia Institute of Technology, alex.hsu@scheller.gatech.edu. Corresponding author.
[†]Board of Governors of the Federal Reserve System, francisco.palomino@frb.gov, phone: 202 452 5220.
[‡]Citigroup, charqian@umich.edu.

Online Appendix

A VAR Estimation

Table I.1 reports coefficients on lagged variables from the baseline VAR estimation. Comparing across the two subsamples, in panels B and C, we notice the responses of monetary policy variables, π, z, and i, are different with respect to lagged monetary policy variables. Output gap and interest rate tend to increase when lagged inflation is high in the early sample (panel B), while they decrease on average in the late sample (panle C). Conversely, inflation reacts positively to lagged interest rate in the early sample, and the reaction flips to negative in the late sample, consistent with the inflation targeting monetary policy aim after 1982. Overall, the VAR coefficient estimates suggest two different macroeconomic regimes in the data between 1961 and 2008.

B Model Selection

Our volatility construction depends on two subjective inputs: the number of lags of the VAR to obtain residuals, and the specific transformation applied to the residuals to obtain volatilities. We consider four different volatility transformations for each macroeconomic variable: absolute and squared errors (directly computed using the residuals), and GARCH absolute and squared errors. GARCH absolute errors estimation is used in our benchmark specification. GARCH squared errors estimation is done by specifying volatility processes $\nu_{2,t}$ that follows

$$\nu_{k,t} = \alpha_k + \sum_{r=1}^{R} \beta_{r,k} \varepsilon_{t-r}^{k} + \sum_{s=1}^{S} \delta_{s,k} \nu_{k,t-s},$$

for $k = 2$.

Looking for some guidance from the data in choosing the benchmark empirical model, we use daily data on the effective Federal Funds rate to calculate interest rate volatility at quarterly frequency. This volatility is compared with the volatility transformations of the nominal short rate from VAR specifications with different lags. Table I.2 summarizes the comparison of data (model-free) and VAR implied volatilities of the nominal short-term interest rate for different VAR lags and volatility transformations. Column (1) shows the correlations of these volatilities, and columns (2) and (3) show the t-statistics and the R^2s, respectively, of regressions of the model-free volatility on the VAR-implied volatilities. In general, the correlations between the two interest rate volatilities are decreasing in the number of lags specified in the VAR. The same is true of the R^2s of the univariate regressions. As the VAR incorporates more lags, the resulting interest rate volatility has less explanatory power on the model-free interest rate volatility series. Evidence from this exercise suggests that a low-lag VAR structure is appropriate. Furthermore, for each of the VAR lag specifications, it is almost always the case that the GARCH-ABS volatility series outperforms the other three methods. Given the AIC lag selection result and Table I.2, we choose a VAR(4) with GARCH absolute value estimated volatility series as the main empirical specification.

As robustness, Figures I.2 and I.3 plot the R^2 and t-statistics of the predictive regressions of stock and 5-year nominal bond returns using conditional volatilities of the short rate, inflation, output gap, and consumption growth. Results in Figure I.2 stem from a VAR(1) specification, while results in Figure I.3 are obtained using the GARCH squared errors estimation. For comparison with Figure 3, in both figures, the left columns present the full sample findings, the middle columns present the early sample findings, and the right columns present the late sample findings.

Figure I.2 subplots (2) and (5) show that interest rate and inflation conditional volatilities have strong predictive power on stock returns in the early sample from 1961Q3 to 1976Q4. The univariate regressions have high R^2, and the regression coefficients are significantly negative in the holding period horizons beyond 3 years. This is in contrast to subplots (3) and (6) showing the lack of predictive power in the late sample from 1982Q1 to 2008Q3. For bond returns in rows 3 and 4 of Figure I.2, interest rate and inflation conditional volatilities again display strong predictive power in the early sample relative to the late sample. Subplot (11) shows the coefficient loadings of future bond returns regressed on interest rate and inflation volatilities are positive and significant at long holding period horizons in the early sample. Although the statistical significance of inflation volatility remains in subplot (12) for the late sample, the R^2 in subplot (9) is much lower than those in subplot (8). In general, the decline in predictability is observed in Figure I.3 when GARCH-SQR is used instead of GARCH-ABS. The evidence is consistent with our main empirical finding in Section 2, suggesting the result is robust to model specification.

C Standard Predictors

Previous literature has identified economic and financial variables with significant predictive power for stock and bond returns. We analyze the predictive power of some of these variables during the sample periods under study. Specifically, we use the dividend yield for the aggregate stock market ($d-p$) and the wealth-consumption ratio (cay) from Lettau and Ludvigson (2001) to predict stock returns, and forward rates implied by the Treasury yield curve (f) to predict bond returns.[1] This analysis is useful to make comparisons to the predictive ability of macroeconomic volatility.

The regressions are

$$r^k_{t\to t+p} = \alpha^k_p + \beta^k_{p,j} Pred^k_t + \varepsilon^k_{j,t+p}, \tag{1}$$

where $r^k_{t\to t+p}$ denotes p-quarter cumulative returns for $k = \{\text{stock, 5-year bond}\}$, and $Pred^j_t$ denotes the predictor for $j = \{d-p, cay, f\}$.

Figure I.1 plots statistics of predictive regressions for the full, early, and late samples, in each column, respectively. Subplots in the first and third rows are for R^2s of the regressions, and subplots in the second and fourth rows are for t-statistics. All t-statistics plots include 1% statistical significance bands at ± 2.57. The horizontal axes denote the horizon of cumulative returns in quarters. The top two rows contain results for regressions of stock returns on dividend yields and stock returns on cay. The bottom two rows contain results of bond returns on forward rates.

For the full sample, left column of Figure I.1, subplot (1) shows that the R^2s of the predictive regressions on the dividend yield and cay are substantial at long return horizons, with significant slope coefficients beyond 4-quarter holding period horizons in subplot (4). The maximal R^2

[1] We use individual forward rates as opposed to the **?** factor since there is no reason to believe the linear relationship of the forward rates is constant over time. Given our prior that bond return predictability has changed over time, it might be inappropriate to apply the forward factor estimated from a sample that is different than what we are using in this paper.

is about 25% at 14 quarters using dividend yield, and the estimated slope coefficients are statistically significant for almost all return horizons. For 5-year bond returns, subplot (7) in the figure shows that forward rates have monotonically increasing predictive power at longer horizons. However, the slope coefficients are generally insignificant at the 1% level beyond 4 quarters.

The middle column of Figure I.1 presents the results for the predictive regressions in the early sample. In subplots (2) and (5), dividend yield and the *cay* factor both have strong predictive power on stock returns in terms of R^2 and t-statistics, especially at the medium horizon. The maximal R^2 reaches 55% at the 8 quarter horizon for dividend yield and roughly 40% at the 12 quarter horizon for *cay*. Statistical significance is especially strong for dividend yield: the coefficient loading when 4-quarter ahead stock returns is regressed on dividend yield has a t-statistic greater than 10. For bond returns in subplots (8) and (11), the predictability evidence is strong at long horizons with a maximal R^2 of more than 50% at 16 quarters. Furthermore, the corresponding t-statistics of the coefficient loadings on the forward rates are highly significant.

The right column of Figure I.1 summarizes the predictive regression results for the late sample. In general, the evidence of predictable stock and bond returns is much weaker relative to the early sample. For stock returns, in subplots (3) and (6), maximal R^2s are substantially lower relative to the regressions R^2s in the early sample. For example, when dividend yield is used as the predictor, the maximal R^2 is around 40% compared with more than 50% in subplot (2). The statistical significance of the slope coefficients on both dividend yield and *cay* considerably declines. In fact, estimated coefficients on dividend yield are only significant at the very short and the very long cumulative return horizons, and they are insignificant between 4- and 12-quarter holding periods. The coefficient loading on *cay* is never significant at the 1% level in subplot (6). For bond return regressions on forwards rates, results in subplots (9) and (12) exhibit reasonably high R^2s and statistically significant slope coefficients. However, the maximal R^2 is at most 35%, lower than the maximal R^2 of more than 50% in the early sample. Overall, the evidence points to weaker predictability on stock and bond returns using standard predictors after the structural break in macroeconomic volatility.

D Predictive Regressions using MCMC Filtered Stochastic Volatilities

In order to test the robustness of the model, apart from the VAR and GARCH methodology described in the main body of the paper, a Time-Varying Parameter Vector Autoregression (TP-VAR), à la Primiceri (2005), is used to obtain the macroeconomic stochastic volatilities. In this approach, the sources of time variation are both the structural coefficients and the variance-covariance matrix of the innovations. Primiceri (2005) develops a modeling strategy for the law of motion of the variance-covariance matrix and proposes a Markov Chain Monte Carlo algorithm for the model likelihood and posterior numerical evaluation.

In the TP-VAR, the drifting coefficients are meant to capture possible nonlinearities or time variation in the lag structure of the model. At the same time, the multivariate stochastic volatility is meant to capture possible heteroskedasticity of the shocks and nonlinearities in the simultaneous relations among the variables of the model. Allowing for time variation both in the coefficients and the variance-covariance matrix leaves it up to the data to determine whether the time variation of the linear structure derives from changes in the size of the shocks or from changes in the propagation mechanism. Bayesian methods are used to evaluate the posterior distributions of the parameters of interest. We refer readers who is interested in the details of our implementation to Primiceri (2005).

Figure I.4 plots the standardized stochastic volatility series for consumption growth, inflation and the nominal short rate over the full sample. Two things stand out: the MCMC filtered volatility series are much smoother relative to their GARCH counterparts, and correlations between series constructed from the two different methodologies are fairly high, especially for the monetary policy variables in subplots (1) and (2). It is worth noting that the TP-VAR is immensely flexible due to the time-varying structural parameters in the VAR, which potentially can soak up some of the variability in volatility that a traditional VAR cannot. Therefore, the TP-VAR produces much more continuous volatility estimates.

Stock and bond return predictive regression results are plotted in Figure I.5. We regress future stock and bond cumulative returns over holding period horizons between 1 and 20 quarters on current period conditional volatility, as in Equation (2), for interest rate, inflation and inflation. Similar to Figure 3, in Figure I.5, we report regression adjusted R^2 and coefficient t-statistics for stock and bond return regressions in the full sample (first column), the early sample (second column) and the late sample (third column). R^2 in the first and third row are plotted on the same scale across samples for ease of comparison. t-statistics in the second and fourth row are plotted relative to 1% confidence bands.

Two things are noteworthy by comparing the early sample with the late sample in Figure I.5. First, MCMC filtered stochastic volatility series, in general, exhibit stronger predictive power of future returns in the early sample relative to the late sample. This is especially true for interest rate and inflation volatilities in predicting stock returns. Using interest rate volatility as the explanatory variable, the regression R^2 reaches a peak of 45% at the long holding period horizon in subplot (2) with a corresponding coefficient t-statistic of about -9 in subplot (5). For inflation volatility, the maximal R^2 and t-statistic are 37% in subplot (2) and roughly -4 in subplot (5), respectively. Whereas in subplots (3) and (6) for the late sample, none of the regression R^2 is greater than 10% at any holding period horizon, and the regression coefficients are never statistically significant at the 1% level. Second, results of bond return predictive regressions are less clearcut, but R^2 in Figure I.5 subplot (8) are generally speaking equal to or greater than those in subplot (9) across holding period horizons when interest rate volatility or consumption growth volatility are used as the independent variable.

Contrasting Figure I.5 from Figure 3, we observe very similar patterns in R^2 and t-statistics across the early and the late sample. The decline in return predictability is more robust for stock returns when MCMC filtered conditional volatilities are utilized as predictors in Figure I.5; while, the same can be said for bond returns when GARCH constructed conditional volatilities are used in Figure 3. Overall, the collective evidence points to a significant fall in return predictability from the sample before 1982 to after.

E Out of Sample Tests

We compute out-of-sample forecasts for the early and late samples. If the early sample (1961Q3 to 1976Q4) exhibits stronger stock and bond return predictability from macroeconomic volatility relative to the late sample (1982Q1 to 2008Q3), the out-of-sample R^2 of the early-sample forecasts should be higher. We rely on the Campbell and Thompson (2008) definition of out-of-sample R^2, which compares the deviation between fitted and realized returns relative to the difference between realized returns and the historical average using the statistic:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r})^2}, \tag{2}$$

where r_t is the realized return, $\hat{r}_t$ is the predicted return, and $\bar{r}$ is the historical average return. If the sum of squared errors of the prediction from the actual return is small, the R^2_{OS} is large. Furthermore, R^2_{OS} takes on positive values only when the forecast from predictive regressions outperforms the historical average.

The forecasts are constructed in "real time," estimating volatilities only with information available at the time of the forecast. First, within each sample, we use the first half of observations to form the initial estimation window. We drop the output gap from the set of variables in the VAR and estimate a 9-variable VAR within the window to find the residuals of consumption growth, inflation, and the nominal short-term rate.[2] Volatilities are estimated using a GARCH absolute error model of the residuals. Second, using the same time window, we run predictive regressions of asset returns on macroeconomic volatility to estimate the volatility loadings. These loadings and macroeconomic volatilities in the last quarter of the estimation window are used to forecast holding-period returns 12-, 16-, and 20-quarters ahead. This procedure is repeated by expanding the estimation window each quarter. The maximal estimation window is the length of the sample minus the holding-period forecast. Finally, we calculate the sum of squared errors implied by the forecasts relative to realized returns, and the historical average return is computed from the beginning of the full sample up until quarter $t-1$.

The resulting R^2_{OS} for the early and the late sample are summarized in Table I.3. Panels A, B, and C report the R^2_{OS} of the 12-, 16-, and 20-quarter holding-period horizon returns, respectively. Forecast errors are smaller for both stock and bond return predictions in the early sample than in the late sample for the three volatility series. This is evidenced by the larger (or less negative) R^2_{OS} in the early sample, except for the 16- and 20-quarter cumulative stock return predictive regressions using interest rate volatility as the predictor. For instance, when the volatility of consumption growth is used to forecast 16-quarter stock returns (panel B, column (1)), the R^2_{OS}s in the early and late samples are 0.31 and -0.42, respectively. For bond returns, column (2) shows that the R^2_{OS} using consumption growth volatility as the predictor is less negative for the early sample (-0.99) relative to the late sample (-1.2). In summary, the out-of-sample forecast exercise provides additional support to our finding using in-sample predictive regressions: both stock and bond cumulative returns across holding-period horizons are less predictable in the Great Moderation using macroeconomic volatilities.

F Model Solution

The model summarized by equations (3)-(8) is solved using the method of undetermined coefficients by guessing the system of linear equations:

$$\begin{aligned}
\pi_t &= \bar{\pi} + \pi_i i_{t-1} + \pi_x x_t + \pi_u u_t + \pi_\epsilon \epsilon_t + \pi_v v_t, \\
z_t &= \bar{z} + z_i i_{t-1} + z_x x_t + z_u u_t + z_\epsilon \epsilon_t + z_v v_t, \\
i_t &= \bar{i} + i_i i_{t-1} + i_x x_t + i_u u_t + i_\epsilon \epsilon_t + i_v v_t, \\
p_{c,t} &= \bar{p}_c + p_{ci} i_{t-1} + p_{cx} x_t + p_{cu} u_t + p_{c\epsilon} \epsilon_t + p_{cv} v_t,
\end{aligned}$$

under the approximation for the return on the wealth portfolio (consumption claim) given by

$$r_{c,t+1} = \bar{\eta}_c + \eta_c p_{c,t+1} + \Delta c_{t+1} - p_{c,t},$$

[2] For the out-of-sample test, we use a VAR(1) instead of a VAR(4) limited by the number of observations we have in the early subsample. The output gap is excluded from the VAR specification since it is constructed by filtering all sample data and not only data available at the time of the return forecast. The results, however, are unaffected if the filtered output gap series is included in the VAR.

where $\eta_c = \frac{\exp(\bar{p}_c)}{1+\exp(\bar{p}_c)}$, and $\bar{\eta}_c = \log(1 + \exp(\bar{p}_c)) - \eta_c \bar{p}_c$. Equilibrium dynamics for the system above consists in finding loadings in the linear equations that satisfy the equilibrium conditions. Specifically, the solution implies finding 24 coefficients to solve 24 equations resulting from the 4 equilibrium conditions (3), (4), (7), and (8). The system of 24 equations is: From loadings on i_{t-1}, we find coefficients π_i, z_i, i_i, and p_{ci} by solving the system:

$$\begin{aligned}
p_{ci} &= \left[\left(1-\frac{1}{\psi}\right) z_i + \eta_c p_{ci}\right] i_i - \left(1-\frac{1}{\psi}\right) z_i, \\
i_i &= \rho + (1-\rho)(\imath_\pi \pi_i + \imath_z z_i), \\
(\gamma z_i + (1-\theta)\eta_c p_{ci} + \pi_i - 1) i_i &= \gamma z_i + (1-\theta) p_{ci}, \\
\pi_i &= \phi_{\pi z} z_i + \beta_\pi \pi_i i_i.
\end{aligned}$$

From loadings on x_t, we find coefficients π_x, z_x, i_x, and p_{cx} by solving the system:

$$\begin{aligned}
p_{cx}(1-\eta_c\phi_x) &= \left[\left(1-\frac{1}{\psi}\right) z_i + \eta_c p_{ci}\right] i_x - \left(1-\frac{1}{\psi}\right)(1-\phi_x) z_x, \\
i_x &= (1-\rho)(\imath_\pi \pi_x + \imath_z z_x), \\
(\gamma z_i + (1-\theta)\eta_c p_{ci} + \pi_i - 1) i_x &= -\left[\gamma(1-(1-\phi_x) z_x + (1-\theta) p_{cx}(\eta_c \phi_x - 1) + \pi_x \phi_x\right], \\
\pi_x &= \phi_{\pi z} z_x + \beta_\pi(\pi_i i_x + \pi_x \phi_x).
\end{aligned}$$

From loadings on u_t, we find coefficients π_u, z_u, i_u, and p_{cu} by solving the system:

$$\begin{aligned}
p_{cu}(1-\eta_c\phi_u) &= \left[\left(1-\frac{1}{\psi}\right) z_i + \eta_c p_{ci}\right] i_u - \left(1-\frac{1}{\psi}\right)(1-\phi_u) z_u, \\
i_u &= (1-\rho)(\imath_\pi \pi_u + \imath_z z_u) + 1, \\
(\gamma z_i + (1-\theta)\eta_c p_{ci} + \pi_i - 1) i_u &= -\left[-\gamma(1-\phi_u) z_u + (1-\theta) p_{cu}(\eta_c \phi_u - 1) + \pi_u \phi_u\right], \\
\pi_u &= \phi_{\pi z} z_u + \beta_\pi(\pi_i i_u + \pi_u \phi_u).
\end{aligned}$$

From loadings on ϵ_t, we find coefficients π_ϵ, z_ϵ, i_ϵ, and $p_{c\epsilon}$ by solving the system:

$$\begin{aligned}
p_{c\epsilon}(1-\eta_c\phi_\epsilon) &= \left[\left(1-\frac{1}{\psi}\right) z_i + \eta_c p_{ci}\right] i_\epsilon - \left(1-\frac{1}{\psi}\right)(1-\phi_\epsilon) z_\epsilon, \\
i_\epsilon &= (1-\rho)(\imath_\pi \pi_\epsilon + \imath_z z_\epsilon), \\
(\gamma z_i + (1-\theta)\eta_c p_{ci} + \pi_i - 1) i_\epsilon &= \gamma(1-\phi_\epsilon) z_\epsilon + (1-\theta) p_{c\epsilon}(\eta_c \phi_\epsilon - 1) - \pi_\epsilon \phi_\epsilon, \\
\pi_\epsilon &= \phi_{\pi z} z_\epsilon + \beta_\pi(\pi_i i_\epsilon + \pi_\epsilon \phi_\epsilon) + 1.
\end{aligned}$$

From loadings on v_t, we find coefficients π_v, z_v, i_v, and p_{cv} by solving the system:

$$\begin{aligned}
p_{cv} = \left[\left(1-\frac{1}{\psi}\right) z_i + \eta_c p_{ci}\right] i_v &- \left(1-\frac{1}{\psi}\right)(1-\phi_\epsilon) z_v + \bar{v}_1 + \frac{1}{\theta}\frac{A_v}{1-\zeta_v A_v}\phi_v, \\
i_v &= (1-\rho)(\imath_\pi \pi_v + \imath_z z_v), \\
(\gamma z_i + (1-\theta)\eta_c p_{ci} + \pi_i - 1) i_v &= \gamma z_v + (1-\theta) p_{cv} + \bar{v}_3 + \frac{1}{\theta}\frac{B_v}{1-\zeta_v B_v}\phi_v, \\
\pi_v &= \phi_{\pi z} z_v + \beta_\pi(\pi_i i_v + \pi_v \phi_v),
\end{aligned}$$

where

$$
\begin{aligned}
\bar{v}_1 &= \frac{\theta}{2}\left[\left(1-\frac{1}{\psi}\right)^2\sigma_{cv} + \left(\left(1-\frac{1}{\psi}\right)z_x + \eta_c p_{cx}\right)^2\sigma_{xv} + \left(\left(1-\frac{1}{\psi}\right)z_u + \eta_c p_{cu}\right)^2\sigma_{uv}\right.\\
&+ \left.\left(\left(1-\frac{1}{\psi}\right)z_\epsilon + \eta_c p_{c\epsilon}\right)^2\sigma_{\epsilon v}\right],\\
A_v &= \theta\left[\left(1-\frac{1}{\psi}\right)z_v + \eta_c p_{cv}\right],\\
\bar{v}_3 &= \frac{1}{2}\Big[\gamma^2\sigma_{cv} + (\gamma z_x + (1-\theta)\eta_c p_{cx} + \pi_x)^2\sigma_{xv} + (\gamma z_u + (1-\theta)\eta_c p_{cu} + \pi_u)^2\sigma_{uv}\\
&+ (\gamma z_\epsilon + (1-\theta)\eta_c p_{c\epsilon} + \pi_\epsilon)^2\sigma_{\epsilon v}\Big],\\
B_v &= -\gamma z_v - (1-\theta)\eta_c p_{cv} - \pi_v.
\end{aligned}
$$

From the constant terms in the equilibrium conditions, we find coefficients $\bar{\pi}$, $\bar{z}$, $\bar{\imath}$, and $\bar{p}_c$ by solving the system:

$$
\begin{aligned}
\bar{p}_c &= \log\beta + \left(1-\frac{1}{\psi}\right)\mu_c + \bar{\eta}_c + \eta_c\bar{p}_c\\
&+ \left[\left(1-\frac{1}{\psi}\right)z_i + \eta_c p_{ci}\right]\bar{\imath} + \bar{a}_1 + \bar{a}_{1v},\\
\bar{\imath} &= (1-\rho)(\bar{\imath} + \imath_\pi\bar{\pi} + \imath_z\bar{z}),\\
(\gamma z_i + (1-\theta)\eta_c p_{ci} + \pi_i - 1)\bar{\imath} &= \theta\log\beta - \gamma\mu_c - (1-\theta)(\bar{\eta}_c + \eta_c\bar{p}_c - \bar{p}_c) - \bar{\pi} + \bar{a}_3 + \bar{a}_{3v},\\
\bar{\pi} &= a_\pi + \phi_{\pi z}\bar{z} + \beta_\pi(\bar{\pi} + \pi_i\bar{\imath}),
\end{aligned}
$$

where

$$
\begin{aligned}
\bar{a}_1 &= \frac{\theta}{2}\left[\left(1-\frac{1}{\psi}\right)^2\bar{\sigma}_c^2 + \left(\left(1-\frac{1}{\psi}\right)z_x + \eta_c p_{cx}\right)^2\bar{\sigma}_x^2 + \left(\left(1-\frac{1}{\psi}\right)z_u + \eta_c p_{cu}\right)^2\bar{\sigma}_u^2\right.\\
&+ \left.\left(\left(1-\frac{1}{\psi}\right)z_\epsilon + \eta_c p_{c\epsilon}\right)^2\bar{\sigma}_\epsilon^2\right],\\
\bar{a}_{1v} &= \frac{1}{\theta}\left[\frac{A_v^2\delta_v\zeta_v^2}{(1-\phi_v)(1-A_v\zeta_v)} - \frac{A_v\delta_v\zeta_v}{1-A_v\zeta_v} - \delta_v\log(1-A_v\zeta_v)\right],\\
\bar{a}_3 &= \frac{1}{2}\Big[\gamma^2\sigma_c^2 + (\gamma z_x + (1-\theta)\eta_c p_{cx} + \pi_x)^2\sigma_x^2 + (\gamma z_u + (1-\theta)\eta_c p_{cu} + \pi_u)^2\sigma_u^2\\
&+ (\gamma z_\epsilon + (1-\theta)\eta_c p_{c\epsilon} + \pi_\epsilon)^2\sigma_\epsilon^2\Big],\\
\bar{a}_{3v} &= \frac{B_v^2\delta_v\zeta_v^2}{(1-\phi_v)(1-B_v\zeta_v)} - \frac{B_v\delta_v\zeta_v}{1-B_v\zeta_v} - \delta_v\log(1-B_v\zeta_v).
\end{aligned}
$$

Some of the equations in the system are not linear and imply multiple solutions. We pick the minimum state variable (MSV) solution according to McCallum (1983) to come up with a unique non-sunspot equilibrium.

The log pricing kernel $m_{t,t+1} \equiv \log M_{t,t+1}$ is

$$
\begin{aligned}
-m_{t,t+1} = {}& \Gamma_0 + \Gamma_i i_{t-1} + \Gamma_x x_t + \Gamma_u u_t + \Gamma_\epsilon \epsilon_t + \Gamma_v v_t + \lambda_c\sigma_{c,t}\varepsilon_{c,t+1} + \lambda_x\sigma_{x,t}\varepsilon_{x,t+1} + \lambda_u\sigma_{u,t}\epsilon_{u,t+1}\\
&+ \lambda_\epsilon\sigma_{\epsilon,t}\varepsilon_{\epsilon,t+1} + \lambda_v\sigma_{v,t}v_{t+1},
\end{aligned}
$$

where

$$
\begin{aligned}
\Gamma_0 &= -\theta \log \beta + \gamma \mu_c + (1-\theta)(\bar{\eta}_c + \eta_c \bar{p}_c - \bar{p}_c) + (\gamma z_i + (1-\theta)\eta_c p_{ci})\bar{i}, \\
\Gamma_i &= \gamma z_i (i_i - 1) + (1-\theta) p_{ci}(\eta_c i_i - 1), \\
\Gamma_x &= \gamma + (\gamma z_i + (1-\theta)\eta_c p_{ci}) i_x + \gamma z_x(\phi_x - 1) + (1-\theta) p_{cx}(\eta_c \phi_x - 1), \\
\Gamma_u &= (\gamma z_i + (1-\theta)\eta_c p_{ci}) i_u + \gamma z_u(\phi_u - 1) + (1-\theta) p_{cu}(\eta_c \phi_u - 1), \\
\Gamma_e &= (\gamma z_i + (1-\theta)\eta_c p_{ci}) i_e + \gamma z_e(\phi_e - 1) + (1-\theta) p_{ce}(\eta_c \phi_e - 1), \\
\Gamma_v &= (\gamma z_i + (1-\theta)\eta_c p_{ci}) i_v - \gamma z_v - (1-\theta) p_{cv}, \\
\lambda_c &= \gamma, \quad \lambda_x = \gamma z_x + (1-\theta)\eta_c p_{cx}, \quad \lambda_u = \gamma z_u + (1-\theta)\eta_c p_{cu}, \\
\lambda_\epsilon &= \gamma z_\epsilon + (1-\theta)\eta_c p_{c\epsilon}, \quad \lambda_v = \gamma z_v + (1-\theta)\eta_c \, p_{cv}.
\end{aligned}
$$

The aggregate stock (dividend claim) return, is approximated as

$$
\log R^r_{d,t+1} =\approx \bar{\eta}_d + \eta_d p_{d,t+1} + \Delta d_{t+1} - p_{d,t},
$$

where $\eta_d = \frac{\exp(\bar{p}_d)}{1+\exp(\bar{p}_d)}$, and $\bar{\eta}_d = \log(1+\exp(\bar{p}_d)) - \eta_c \bar{p}_d$. The solution for the price dividend ratio is

$$
p_{d,t} = \bar{p}_d + p_{di} i_{t-1} + p_{dx} x_t + p_{du} u_t + p_{d\epsilon} \epsilon_t + p_{dv} v_t,
$$

with coefficients

$$
\begin{aligned}
\bar{p}_d &= -\Gamma_0 + \bar{\eta}_d + \eta_d \bar{p}_d + (\eta_d p_{di} + \phi_{dc} z_i)\bar{i} + \mu_c \\
&+ \bar{b}_{dv} + \frac{C_v^2 \delta_v \zeta_v^2}{(1-\phi_v)(1-C_v\zeta_v)} - \frac{C_v \delta_v \zeta_v}{1 - C_v \zeta_v} - \delta_v \log(1 - C_v \zeta_v), \\
p_{di} &= (-\Gamma_i + \phi_{dc} z_i (i_i - 1))/(1 - \eta_d i_i), \\
p_{dx} &= (-\Gamma_x + (\eta_d p_{di} + \phi_{dc} z_i) i_x + \phi_{dc}(1 + z_x(\phi_x - 1)))/(1 - \eta_d * \phi_x), \\
p_{du} &= (-\Gamma_u + (\eta_d p_{di} + \phi_{dc} z_i) i_u + \phi_{dc} z_u (\phi_u - 1))/(1 - \eta_d \phi_u), \\
p_{d\epsilon} &= (-\Gamma_\epsilon + (\eta_d p_{di} + \phi_{dc} z_i) i_\epsilon + \phi_{dc} z_e (\phi_\epsilon - 1))/(1 - \eta_d \phi_\epsilon), \\
p_{dv} &= \bar{a}_d + \bar{a}_{dv} - \frac{(\lambda_v - \phi_{dc} z_v - \eta_d p_{dv})\phi_v}{1 + (\lambda_v - \phi_{dc} z_v - \eta_d p_{dv})\zeta_v},
\end{aligned}
$$

where

$$
\begin{aligned}
\bar{a}_d &= -\Gamma_v + (\eta_d p_{di} + \phi_{dc} z_i) i_v - \phi_d c z_v + \frac{C_v \phi_v}{1 - C_v \zeta_v}, \\
\bar{a}_{dv} &= \frac{1}{2}\Big[(\lambda_c - \sigma_{dc})^2 \sigma_{cv} + (\lambda_x - \phi_{dc} z_x - \eta_d p_{dx})^2 \sigma_{xv} + (\lambda_u - \phi_{dc} z_u - \eta_d p_{du})^2 \sigma_{uv} \\
&+ (\lambda_\epsilon - \phi_{dc} z_\epsilon - \eta_d p_{d\epsilon})^2 \sigma_{\epsilon v} + \sigma_{dv}\Big], \\
\bar{b}_{dv} &= \frac{1}{2}\Big[(\lambda_c - \sigma_{dc})^2 \bar{\sigma}_c^2 + (\lambda_x - \phi_{dc} z_x - \eta_d p_{dx})^2 \bar{\sigma}_x^2 + (\lambda_u - \phi_{dc} z_u - \eta_d p_{du})^2 \bar{\sigma}_u^2 \\
&+ (\lambda_\epsilon - \phi_{dc} z_\epsilon - \eta_d p_{d\epsilon}^2 \bar{\sigma}_{\epsilon v}^2 + \bar{\sigma}_d^2\Big], \\
C_v &= \lambda_v - \phi_{dc} z_v - \eta_d p_{dv}.
\end{aligned}
$$

The real risk-free rate is

$$
r_t = \bar{r} + + r_i i_{t-1} + r_x x_t + r_u u_t + r_\epsilon \epsilon_t + r_v v_t,
$$

where

$$
\begin{aligned}
\bar{r} &= \Gamma_0 - \frac{1}{2}\left(\lambda_c^2 \bar{\sigma}_c^2 + \lambda_x^2 \bar{\sigma}_x^2 + \lambda_u^2 \bar{\sigma}_u^2 + \lambda_\epsilon^2 \bar{\sigma}_\epsilon^2\right) + \delta_v \log(1 + \lambda_v \zeta_v) - \frac{\lambda_v^2 \zeta_v^2 \delta_v}{(1-\phi_v)(1+\lambda_v\zeta_v)} - \frac{\lambda_v \delta_v \zeta_v}{1 + \lambda_v \zeta_v}, \\
r_i &= \Gamma_i, \quad r_x = \Gamma_x, \quad r_u = \Gamma_u, \quad r_\epsilon = \Gamma_\epsilon, \\
r_v &= \Gamma_v - \frac{1}{2}\left(\lambda_c^2 \sigma_{cv} + \lambda_x^2 \sigma_{xv} + \lambda_u^2 \sigma_{uv} + \lambda_\epsilon^2 \sigma_{\epsilon v}\right) + \frac{\lambda_v \phi_v}{1 + \lambda_v \zeta_v}.
\end{aligned}
$$

Nominal bond yields are given by

$$y_t^{(n)} = \frac{1}{n}\left(\mathcal{A}_n + \mathcal{B}_{i,n} i_{t-1} + \mathcal{B}_{x,n} x_t + \mathcal{B}_{u,n} u_t + \mathcal{B}_{\epsilon,n}\epsilon_t + \mathcal{B}_{v,n} v_t\right).$$

From the recursive bond pricing equation, the coefficients can be found recursively as:

$$\begin{aligned}
\mathcal{A}_n &= \mathcal{A}_{n-1} + \Gamma_0 + \bar{\pi} - \frac{1}{2}[\lambda_c^2\bar{\sigma}_c^2 + (\lambda_x + \pi_x + \mathcal{B}_{x,n-1})^2\bar{\sigma}_x^2 + (\lambda_u + \pi_u + \mathcal{B}_{u,n-1})^2\bar{\sigma}_u^2 \\
&+ (\lambda_\epsilon + \pi_\epsilon + \mathcal{B}_{\epsilon,n-1})^2\bar{\sigma}_\epsilon^2] + \frac{D_v^2\delta_v\zeta_v^2}{(1-\phi_v)(1-D_v\zeta_v)} - \frac{D_v\delta_v\zeta_v}{1-D_v\zeta_v} - \delta_v\log(1-D_v\zeta_v), \\
\mathcal{B}_{i,n} &= \Gamma_i + \mathcal{B}_{i,n-1} i_i, \\
\mathcal{B}_{x,n} &= \Gamma_x + \pi_x\phi_x + \mathcal{B}_{i,n-1} i_x + \mathcal{B}_{x,n-1}\phi_x, \\
\mathcal{B}_{u,n} &= \Gamma_u + \pi_u\phi_u + \mathcal{B}_{i,n-1} i_u + \mathcal{B}_{u,n-1}\phi_u, \\
\mathcal{B}_{\epsilon,n} &= \Gamma_\epsilon + \pi_\epsilon\phi_\epsilon + \mathcal{B}_{i,n-1} i_\epsilon + \mathcal{B}_{\epsilon,n-1}\phi_\epsilon, \\
\mathcal{B}_{v,n} &= \Gamma_v + \pi_v\phi_v + \mathcal{B}_{i,n-1} i_v + \frac{D_v\phi_v}{1+D_v\zeta_v} - \frac{1}{2}[\lambda_c^2\sigma_{cv} + (\lambda_x + \pi_x + \mathcal{B}_{x,n-1})^2\sigma_{xv} \\
&+ (\lambda_u + \pi_u + \mathcal{B}_{u,n-1})^2\sigma_{uv} + (\lambda_\epsilon + \pi_\epsilon + \mathcal{B}_{\epsilon,n-1})^2\sigma_{\epsilon,v}],
\end{aligned}$$

where

$$D_v = -(\lambda_v + \pi_v + \mathcal{B}_{v,n-1}),$$

and $\mathcal{A}_0 = \mathcal{B}_{k,0} = 0$.

G Experiments with Recalibration

We use data for the subsample 1982Q1 - 2008Q3 to learn whether the joint changes in macroeconomic volatility dynamics and return predictability observed during this period, relative to the subsample 1961Q1 - 1976Q4, are consistent with changes in policy parameters, changes in properties of fundamental shocks, or both. Specifically, the experiments consist of a set of calibrations in which certain structural parameters are allowed to change from the baseline (early sample) calibration to match the moments targeted in the calibration for the 1982Q1 - 2008Q3 subsample, while keeping the remaining parameters at their baseline levels.[3] The purpose of this exercise is to determine how well changes in a reduced set of parameters can capture changes in targeted moments. In particular, we are interested in understanding potential economic drivers of the following changes: the reduction of consumption growth and inflation volatility that was accompanied by an increase in interest-rate volatility, the reduction in the autocorrelation of inflation, a less negative correlation between consumption growth and inflation, a positive (from negative) correlation of consumption growth and the nominal interest rate, a larger average bond yield (term) spread, and the reduction in the asset return predictability explained by macroeconomic volatility.

The experiments are divided into four groups: changes only to policy parameters, changes to policy parameters and the Phillips curve parameter, changes only to shock parameters, and changes to shock parameters accompanied by changes in parameters governing the policy rule and the Phillips curve. For clarity, policy parameters group the smoothing parameter (ρ) the responses to inflation ($\imath_\pi$), and changes in the output gap ($\imath_z$) in the monetary policy rule. For the Phillips curve, we focus on the coefficient linking inflation to the real economy ($\phi_{\pi z}$). This parameter can be affected by pricing policies in the production sector.

[3]The procedure is similar to the one used to obtain the baseline calibrations.

Table I.4 reports the results of the experiments. For convenience, the data moments for the early and late samples are reported in the first two columns of the table. Again, on the macroeconomic side, we focus on the standard deviations of consumption growth, inflation, and the nominal short rate, as well the autocorrelations of and correlations between these three endogenous variables. The baseline line model calibration for the early sample is shown in Column (1). These calibrated model moments are directly taken from Panel A in Table 6.

Model moments of the policy rule only experiment is shown in Table I.4 Column (2). In this case, ρ, $\imath_\pi$, and $\imath_z$ are allowed to change from their early sample calibrated values while keeping all other parameters fixed. The corresponding estimated parameter values can be found in Table I.5 Column (2). Examining the moments in Table I.4, by only changing the policy rule parameters, the volatilities of consumption growth (0.94% to 1.21%) and inflation (0.43% to 0.66%) actually increase from Columns (1) to (2), the autocorrelations of consumption growth (0.20 to 0.12) and interest rate (0.96 to 0.84) decline, the correlation of consumption growth and inflation flips from negative to positive (-0.44 to 0.10). These changes in model implied moments are all counter-factual to the changes observed in data moving from the early sample to the late sample. Despite the fact that the estimated Taylor rule coefficient is much closer to the value found in the literature (1.5793), as shown in Column (2) of Table I.5, the policy rule only experiment fails to capture the dynamic change in macroeconomic moments.

Next, we let the Phillips curve parameter, $\phi_{\pi z}$, to also be flexible along side the policy rule parameters. Model implied moments from this experiment is shown in Table I.4 Column (3), and the corresponding estimates are presented in Table I.5 Column (3). With greater values of $\imath_\pi$ and $\phi_{\pi z}$, this experiment still results in higher volatilities for consumption growth (0.94% to 1.34%) and inflation (0.43% to 0.96%), lower autocorrelations for consumption growth (0.20 to 0.06) and interest rate (0.96 to 0.80). The correlation between consumption growth and inflation is even more positive (0.32) relative to the policy rule only experiment. Lastly, the average term structure is significantly downward sloping at -1.25%. By letting the policy rule and Phillips curve parameters to be estimated jointly, the model does not produce sensible moments to match those observed in the data.

In the third experiment, we focus on the shock parameters, and these parameters can be found in Table I.5 Column (4). Notice that we fix the underlying autoregressive gamma volatility parameters (ϕ_v and ζ_v) from their estimated values in the early sample baseline calibration. The idea is that we want to investigate if the "structure" of the volatility process can impact return predictability, rather than a simple decline in the underlying volatility process. The re-estimated parameters govern volatility processes associated with consumption growth, long-run mean of consumption growth, the monetary policy shock, the cost-push shock in the Phillips curve, and dividend growth. Model implied moments are shown in Column (4) of Table I.4. In this case, the estimated model is able to produce the less negative correlation between consumption growth and inflation (-0.44 to -0.11), but this is at the cost of generating a negative correlation between consumption growth and the nominal short rate (-0.04), contrary to the late sample data. Furthermore, changes in macroeconomic volatilities and autocorrelations are generally moving in the wrong direction between Column (1) to Column (4): consumption growth and inflation standard deviations rise, consumption growth autocorrelation increase, and the term spread falls. Overall, the shocks only experiment, although more promising than the policy only experiment, is not sufficient in producing all the desired moment changes from the early sample to the late sample.

As the last experiment, we let all parameters associated the policy rule, the Phillips curve, and the shock structure be re-estimated. This essentially only keeps the preference parameters and the autoregressive gamma volatility process parameters fixed at their early sample calibration values. The goal is to see if a combination of policy rule and shock structure changes is enough to generate the observed movement in macroeconomic moments similar when compared with the data. Moments from this experiment are tabulated in Table I.4 Column (5). Relative to the early sample baseline calibration shown in Column (1), when policy rule parameters and shock parameters are flexible, the model does a decent job in the following dimensions: autocorrelations of consumption growth rises (0.20 to 0.55), the autocorrelation of inflation falls (0.95 to 0.57), the correlation between consumption growth and inflation becomes less negative (-0.44 to -0.12), the correlation of consumption growth and interest rate turns positive (-0.44 to 0.41), and the term spread increases (0.23% to 0.46%). More importantly, in terms of asset return predictability, model implied predictive regression R^2 are much lower in Column (5) when compared with those in Column (1) where inflation and interest rate volatilities are used as predictors.[4] It is important to point out here that the estimated persistence of long run risk ($\phi_x = 0.2061$) is small in Column (5). This is because long run risk generates negative term premium as shown in Rudebusch and Swanson (2012). Since the model is attempting to fit the large term spread in the late sample data, the calibration chooses to downplay the long run risk mechanism by picking a small persistence parameter.

The one downside of experiment four is the fact that volatilities of consumption growth and inflation are too high, exceeding their values of the early sample calibration. To achieve lower macroeconomic volatility, it is necessary to also let the underlying autoregressive gamma volatility process, v_t, to be re-estimated, which is the case for the late sample calibration shown in Column (6) of Table I.4. In the late sample calibration, standard deviations of consumption growth (0.94% to 0.67%) and inflation (0.43% to 0.35%) both decline from the early sample calibration, while autocorrelations, correlations, and risk premia change in a consistent manner as those in the data. Table I.5 Column (6) shows the estimated parameter values for the late sample calibration. Indeed, the persistence ($\phi_v = 0.0784$) and the scale ($\zeta_v = 0.4727$) parameters of the autoregression gamma volatility process are both smaller relative to their estimated values from the early sample calibration. This implies lower conditional mean of v_t and lower macroeconomic volatility in the model.

From these experiments, we come to the following conclusion. First, changes in the policy rule and Phillips curve parameters are not likely to be the main driver of the decline in return predictability from the early to late sample. The fit of macroeconomic moments are very poor, the average term structure is downward sloping, and the predictive regression R^2 are hardly affected. Second, changes in the volatility shock structure is a more promising explanation. In particular, it generates significant decreases in predictive regression R^2. The one weakness of the shocks only explanation is that the term spread is lower than that of the early sample and close to zero. Third, the combination of changes in policy rule, Phillips curve and shock structure can capture most of the targeted moment shifts, but the resulting macroeconomic variables are too volatile. Finally, by letting the underlying volatility process to be modified, the model does a good job in illustrating the crucial elements driving the decline in return predictability.

H Policy Rule Comparative Statics

Figure I.6 displays comparative statics of several targeted moments for changes in the interest-rate policy rule parameters ρ, $\imath_\pi$, and $\imath_z$ using the late sample calibration as the baseline. The four columns on the right show how the R^2s of predictive regressions of 5-year equity and bond returns on inflation and interest-rate conditional volatility change with the policy rule parameters. The main message from the figure is that the R^2's in the predictive regressions

[4] Recall that when we calibrate the model to the late sample, we do not target predictive regression R^2 using consumption growth volatility as the independent variable.

increase when the responses to inflation and the output gap, $\imath_\pi$ and $\imath_z$, respectively, are stronger, but decrease if interest-rate smoothing, ρ increases. The predictive ability of macroeconomic volatility increases because volatility shocks explain a larger variation of equity and bond returns as the policy becomes more responsive to economic conditions. However, all these effects on R^2s are very small in the late sample calibration. That is, the return predictive ability of macroeconomic volatility is low and not very sensitive to changes in the policy rule.

The left two columns in the figure show the impact of the policy rule parameters on the average equity risk premium ($E[r_d - i]$) and the average 5-year nominal term spread ($E[y^{(20)} - i]$), respectively. Policies that are more responsive to inflation and the output gap or that have a smaller interest-rate smoothing component reduce the volatility of consumption growth and reduce the equity premium. For the nominal term spread, $E[y^{(20)} - i]$, however, larger values of $\imath_\pi$ and $\imath_z$ have opposite effects. Both stronger responses imply a reduction in the inflation risk premium that reduce the average term spread. However, an increase in the policy rule inflation response has a significant effect reducing the negative real term premium, increasing the average nominal spread. The second effect dominates when the inflation response is stronger and then the average term spread increases.

I Tables and Figures - Additional Material

Table I.1: **VAR Coefficients on the First Lagged Variables and the Constant Term**
VAR regression coefficients of the benchmark 10-variable model. Elements of the VAR, in order, are: output growth (Δy), consumption growth (Δc), hours growth (Δh), wage growth (Δw), investment growth (Δinv), government spending growth (Δg), government revenue growth ($\Delta \tau$), inflation (π), output gap (z), and the nominal short-term rate (i). Four lags are included in the VAR, but only the loadings on the first lag are shown. For brevity, only three equations pertinent to the predictive regressions are displayed: consumption growth, inflation, and the nominal short rate. Panel A covers the full sample from 1961Q3 to 2008Q3, panel B covers the early subsample from 1961Q3 to 1976Q4, and panel C covers the late subsample from 1982Q1 to 2008Q3.

	Const.	Δy_{t-1}	Δc_{t-1}	Δh_{t-1}	Δw_{t-1}	Δinv_{t-1}	Δg_{t-1}	$\Delta \tau_{t-1}$	π_{t-1}	i_{t-1}
Panel A: Full Sample 1961Q3 to 2008Q3										
Δc_t	0.01	-0.09	-0.13	0.05	-0.05	0.01	0.13	0.02	0.00	0.03
π_t	0.15	-0.02	0.03	0.04	0.03	0.01	0.11	-0.03	0.20	-0.02
i_t	-0.37	-0.13	-0.13	0.04	-0.10	0.02	-0.18	-0.01	-0.57	-0.05
Panel B: Early Sample 1961Q3 to 1976Q4										
Δc_t	0.63	-0.22	-0.16	0.28	0.40	0.01	0.46	0.00	0.40	0.04
π_t	0.16	0.32	-0.24	-0.07	-0.23	-0.06	0.00	-0.06	0.13	0.09
i_t	2.20	-0.40	0.12	-0.21	-0.54	0.16	-0.93	0.15	0.65	0.07
Panel C: Late Sample 1982Q1 to 2008Q3										
Δc_t	-0.15	-0.03	-0.16	-0.01	-0.04	0.02	0.12	-0.02	0.19	0.08
π_t	0.00	0.13	-0.11	-0.11	0.02	-0.01	0.04	-0.01	0.33	-0.08
i_t	-0.38	0.27	-0.32	-0.18	-0.22	-0.05	-0.02	0.00	-0.12	0.07

Table I.2: **Comparison between VAR-implied and the Model-free Measures of Interest Rate Stochastic Volatility**

Unconditional correlations as well as univariate regression t-statistics and R^2 between interest rate stochastic volatilities constructed from the 10-variable VAR and daily data. The VAR-implied measure is constructed from the residuals of the interest rate equation, applying one of these four transformations: absolute values, squared values, GARCH absolute values, and GARCH square values. The model-free measure uses daily interest rate data, and volatility is calculated every quarter. The full sample is from 1961Q3 to 2008Q3.

	(1) $Correlations$	(2) $t - Statistics$	(3) R^2
VAR(1)			
ABS	0.572	4.908	0.324
SQR	0.431	2.890	0.181
GARCH-ABS	0.724	6.424	0.521
GARCH-SQR	0.612	4.625	0.372
VAR(2)			
ABS	0.561	4.069	0.311
SQR	0.472	2.565	0.218
GARCH-ABS	0.650	8.795	0.419
GARCH-SQR	0.538	5.210	0.286
VAR(3)			
ABS	0.419	2.538	0.171
SQR	0.389	1.758	0.147
GARCH-ABS	0.565	4.548	0.315
GARCH-SQR	0.479	3.202	0.225
VAR(4)			
ABS	0.379	2.068	0.139
SQR	0.371	1.637	0.133
GARCH-ABS	0.504	4.321	0.250
GARCH-SQR	0.449	3.691	0.197
VAR(5)			
ABS	0.363	2.065	0.127
SQR	0.370	1.616	0.132
GARCH-ABS	0.425	4.301	0.176
GARCH-SQR	0.429	3.281	0.179
VAR(6)			
ABS	0.314	1.764	0.093
SQR	0.369	1.582	0.131
GARCH-ABS	0.436	4.259	0.185
GARCH-SQR	0.448	3.824	0.197
VAR(7)			
ABS	0.287	1.661	0.078
SQR	0.348	1.536	0.116
GARCH-ABS	0.340	3.191	0.111
GARCH-SQR	0.459	3.954	0.207
VAR(8)			
ABS	0.256	1.610	0.060
SQR	0.317	1.448	0.095
GARCH-ABS	0.220	1.831	0.043
GARCH-SQR	0.283	1.826	0.075

Table I.3: **Out of Sample Forecast** R^2

Out of sample return forecast performed with an expanding estimation window within the early (1961Q3-1976Q4) and the late (1982Q1-2008Q3) sample. Conditional volatilities of consumption growth (Δc), inflation (π), and the nominal short-term rate (i) are GARCH-ABS estimates of a 9-vector VAR residuals (output gap is dropped), using only the first half of observations in the given sample as the initial estimation window. Univariate predictive regressions are employed within the window to estimate the predictive coefficient. In each iteration, the estimation is done by expanding the window by one quarter. Return forecasts are done in "real time" for horizons of 12, 16, and 20 quarters. The R^2 is calculated according to Campbell and Thompson (2008).

	Conditional Volatility	(1) Stock Out of Sample R^2	(2) Bond Out of Sample R^2
Panel A: 12 Quarter Ahead Cumulative Return			
Early Sample	Δc	**0.2182**	-0.4519
	π	-0.0089	-0.4373
	i	-0.1526	-0.4389
Late Sample	Δc	-0.2545	-0.9809
	π	-0.4942	-1.6917
	i	-0.3319	-1.7902
Panel B: 16 Quarter Ahead Cumulative Return			
Early Sample	Δc	**0.3094**	-0.9859
	π	-0.3476	-1.1843
	i	-0.6400	-1.0283
Late Sample	Δc	-0.4245	-1.1966
	π	-0.6372	-2.4359
	i	-0.4358	-2.4320
Panel C: 20 Quarter Ahead Cumulative Return			
Early Sample	Δc	**0.0042**	-1.9684
	π	-0.5535	-1.8582
	i	-1.0908	-1.3643
Late Sample	Δc	-0.7253	-1.3456
	π	-0.9676	-3.0153
	i	-0.7215	-3.0855

Table I.4: **Model Experiments - Relevant Moments**

Data statistics are for the subsamples 1961Q3-1976Q4 and 1982Q1-2008Q3. Model moments for the calibrations are computed based on 5,000 simulations of 62 and 107 periods each (sample size), respectively, using the parameter values in Table 5 for the respective subsample. Model moments for all experiments are computed based on 5,000 simulations of 107 periods each, using the parameters in Table 5 for the first subsample, except for the parameters that are changed in the experiment. "SD" is the standard deviation. "AC" is the first-order autocorrelation. "CVol" is the conditional volatility. Predictability R^2's correspond to predictive regressions of 20-quarter cumulative stock and 5-year bond nominal returns, r_d and $r^{(20)}$, respectively. Standard deviations and R^2's are reported as percentage.

			(1)	(2)	(3)	(4)	(5)	(6)
	Data		Model					
			Baseline	Experiments				Baseline
			1961-1976 Calibration	Policy Rule Only	Policy Rule + $\phi_{\pi,z}$	Shocks Only	Policy + Shocks + $\phi_{\pi,z}$	1982-2008 Calibration
Moments	1961-1976	1982-2008						
SD(Δc)	0.52	0.38	0.92	1.21	1.34	1.11	1.07	0.67
SD(π)	0.65	0.28	0.37	0.66	0.96	0.74	0.46	0.35
SD(i)	1.50	2.58	0.70	0.47	0.63	0.60	0.57	1.14
SD(Δd)	10.25	8.06	9.23	2.30	2.74	8.52	14.83	4.95
AR(Δc)	0.36	0.42	0.15	0.12	0.06	0.12	0.55	0.14
AR(π)	0.86	0.61	0.93	0.70	0.55	0.82	0.57	0.62
AR(i)	0.89	0.95	0.94	0.84	0.80	0.99	0.60	0.60
corr($\Delta c, \pi$)	-0.41	-0.08	-0.39	0.10	0.32	-0.11	-0.12	-0.08
corr($\Delta c, i$)	-0.34	0.28	-0.39	0.29	0.41	-0.04	0.41	0.10
corr(π, i)	0.77	0.52	0.99	0.57	0.53	0.84	0.83	0.89
$\mathbb{E}[y^{(20)} - i]$	0.77	1.39	0.92	-0.64	-1.25	0.05	0.46	1.61
$\mathbb{E}[r_d - i]$	1.60	6.10	4.22	1.26	1.24	0.75	1.07	2.18
Predictive Regression R^2s								
r_d on $CVol$ of:								
Δc	0.51	0.20	2.82	2.05	2.51	1.17	1.15	1.21
π	5.18	0.26	3.09	4.11	3.74	1.19	1.09	1.15
i	12.24	1.43	3.31	3.64	3.39	1.41	1.10	1.18
$r^{(20)}$ on $CVol$ of:								
Δc	0.02	0.55	2.70	2.33	2.14	1.19	1.17	1.13
π	11.94	4.87	4.96	5.17	2.95	1.20	1.22	1.91
i	17.10	1.15	7.65	4.50	2.64	1.50	1.20	1.78

Table I.5: **Model Experiments - Estimated Parameter Values**

Parameter values not reported in the table are set as in Table 5 for the 1961-1976 calibration.

	(1)	(2)	(3)	(4)	(5)	(6)
		Model				
	Baseline	Experiments				Baseline
Parameter	Early Sample Calibration	Policy Rule Only	Policy Rule + $\phi_{\pi,z}$	Shocks Only	Policy + Shocks + $\phi_{\pi,z}$	Late Sample Calibration
β	0.9982					0.9971
γ	16.1281					23.6498
ψ	1.9999					1.9943
$\bar{\sigma}_c \times 10^3$	5.5263			6.8545	0.0187	3.9218
$\sigma_{cv}/\bar{\sigma}_c^2$	-4.9999			-4.3910	-0.3431	-2.8780
ϕ_x	0.8123			0.8568	0.2061	0.0001
$\bar{\sigma}_x \times 10^3$	3.2150			2.6681	13.777	3.6593
$\sigma_{xv}/\bar{\sigma}_x^2$	1.2646			1.2354	0.0163	4.9999
$\phi_{\pi z}$	0.2247		0.4984		0.8999	0.7323
β_π	0.9999					0.9500
ρ	0.9049	0.0946	0.0574		0.6901	0.6302
$\bar{\imath}$	0.0010				-0.0119	-0.0047
$\imath_\pi$	1.0359	1.5793	1.6201		2.9999	2.5770
$\imath_z$	-1.9999	-1.0899	-1.5568		1.9999	1.9996
ϕ_u	0.0000			0.9994	0.9271	0.8172
$\bar{\sigma}_u \times 10^7$	0.0000			36.925	55.938	11967
$\sigma_{uv}/\bar{\sigma}_u^2$	0.0000			-4.9938	4.9030	-0.8234
ϕ_ϵ	0.0023			0.0001	0.9999	0.7758
$\bar{\sigma}_\epsilon \times 10^3$	0.1742			1.5914	0.8961	1.3878
$\sigma_{\epsilon v}/\bar{\sigma}_\epsilon^2$	4.9999			-4.5060	0.0300	1.7319
ϕ_{dc}	4.0467					9.8593
$\bar{\sigma}_d \times 10^3$	94.6174			76.916	0.0999	1.0000
σ_{dc}	-0.2439					-4.9999
σ_{dv}	3.9574			4.8596	-4.9653	-3.9354
ϕ_v	0.6056					0.0784
ζ_v	1.9569					0.4727

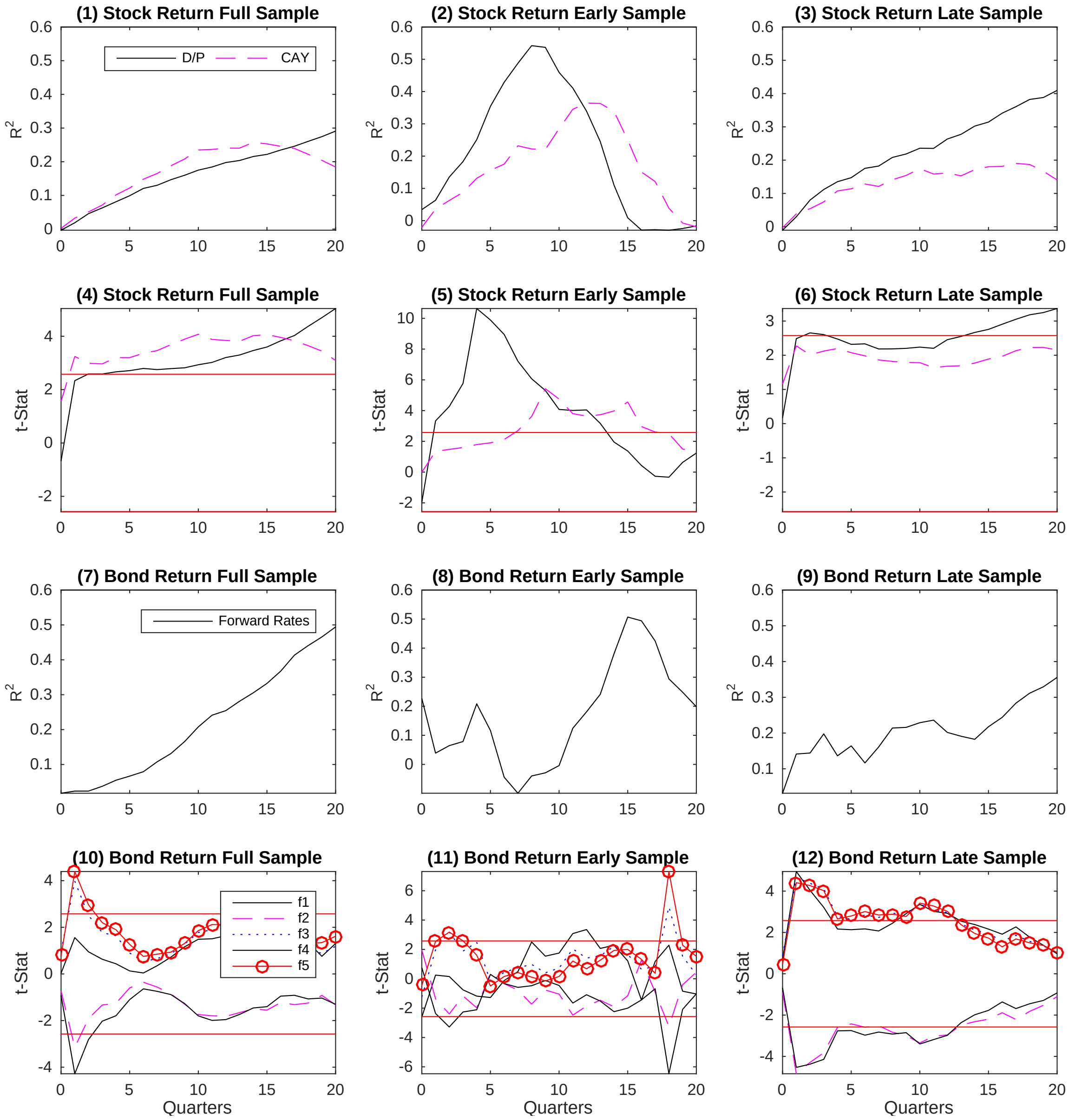

Figure I.1: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961Q3 to 2008Q3, the early sample from 1961Q3 to 1976Q4, and the late sample from 1982Q1 to 2008Q3. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first two rows) and nominal bonds (the bottom two rows). The regressors for equity returns are dividend yield and *cay*, respectively. The regressors for bond returns are **?** forward rates. Macroeconomic volatilities are not included in the predictive regressions. Odd rows report adjusted R^2, and even rows report coefficient t-statistics with 1% confidence interval bands. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics.

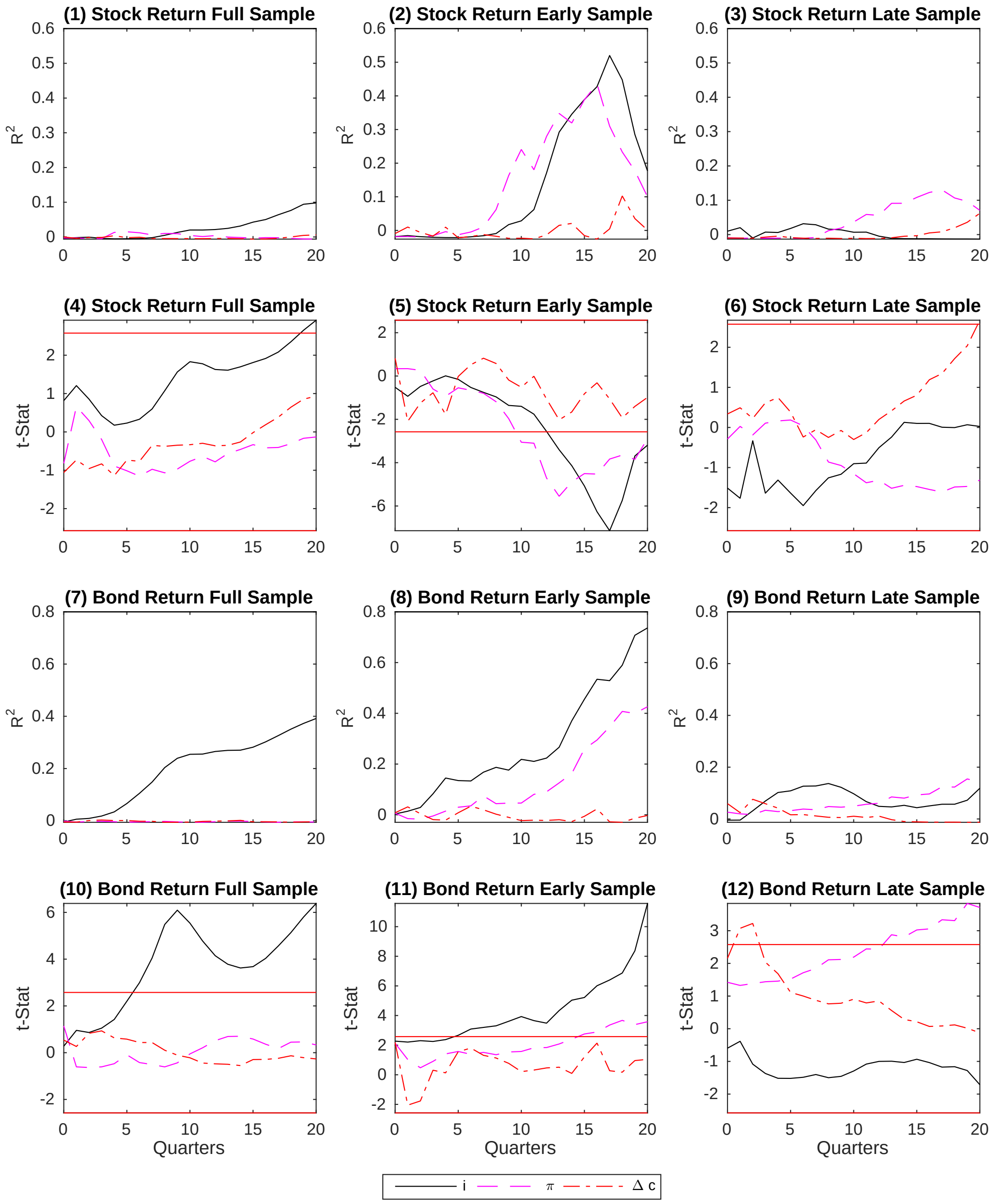

Figure I.2: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961Q3 to 2008Q3, the early sample from 1961Q3 to 1976Q4, and the late sample from 1982Q1 to 2008Q3. The dependent variables are cumulative log returns from time t up to $t + 20$, or up to 5 years, for equity (the first two rows) and nominal bonds (the bottom two rows). Univariate regressions in which the explanatory variables are volatilities of the nominal short rate (i), inflation (π), and consumption growth (Δc) are used. Odd rows report adjusted R^2, and even rows report coefficient t-statistics with 1% confidence interval bands. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Volatility construction employs VAR(1) and GARCH absolute value.

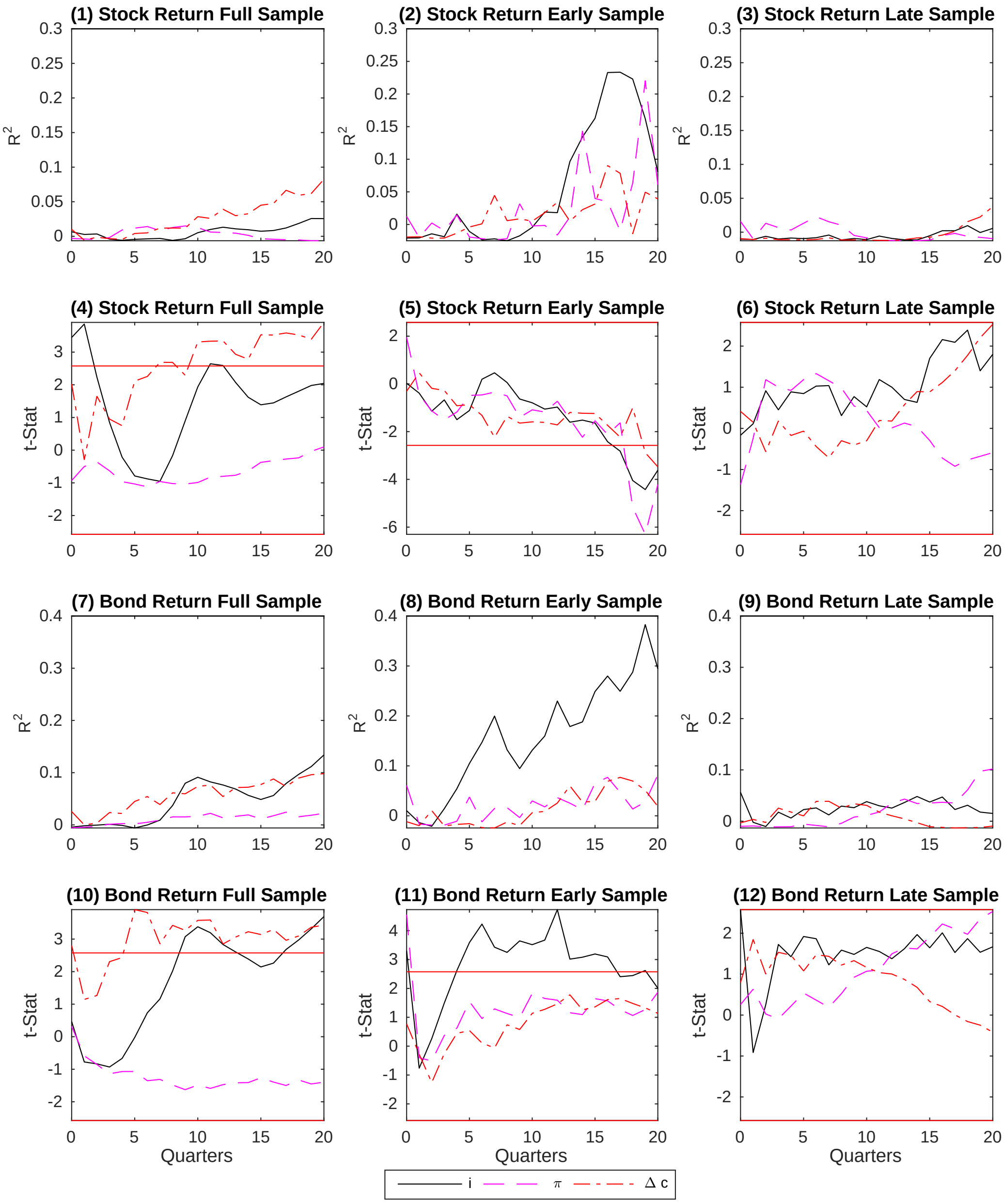

Figure I.3: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961Q3 to 2008Q3, the early sample from 1961Q3 to 1976Q4, and the late sample from 1982Q1 to 2008Q3. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first two rows) and nominal bonds (the bottom two rows). Univariate regressions in which the explanatory variables are volatilities of the nominal short rate (i), inflation (π), and consumption growth (Δc) are used. Odd rows report adjusted R^2, and even rows report coefficient t-statistics with 1% confidence interval bands. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Volatility construction employs VAR(4) and GARCH squared residuals.

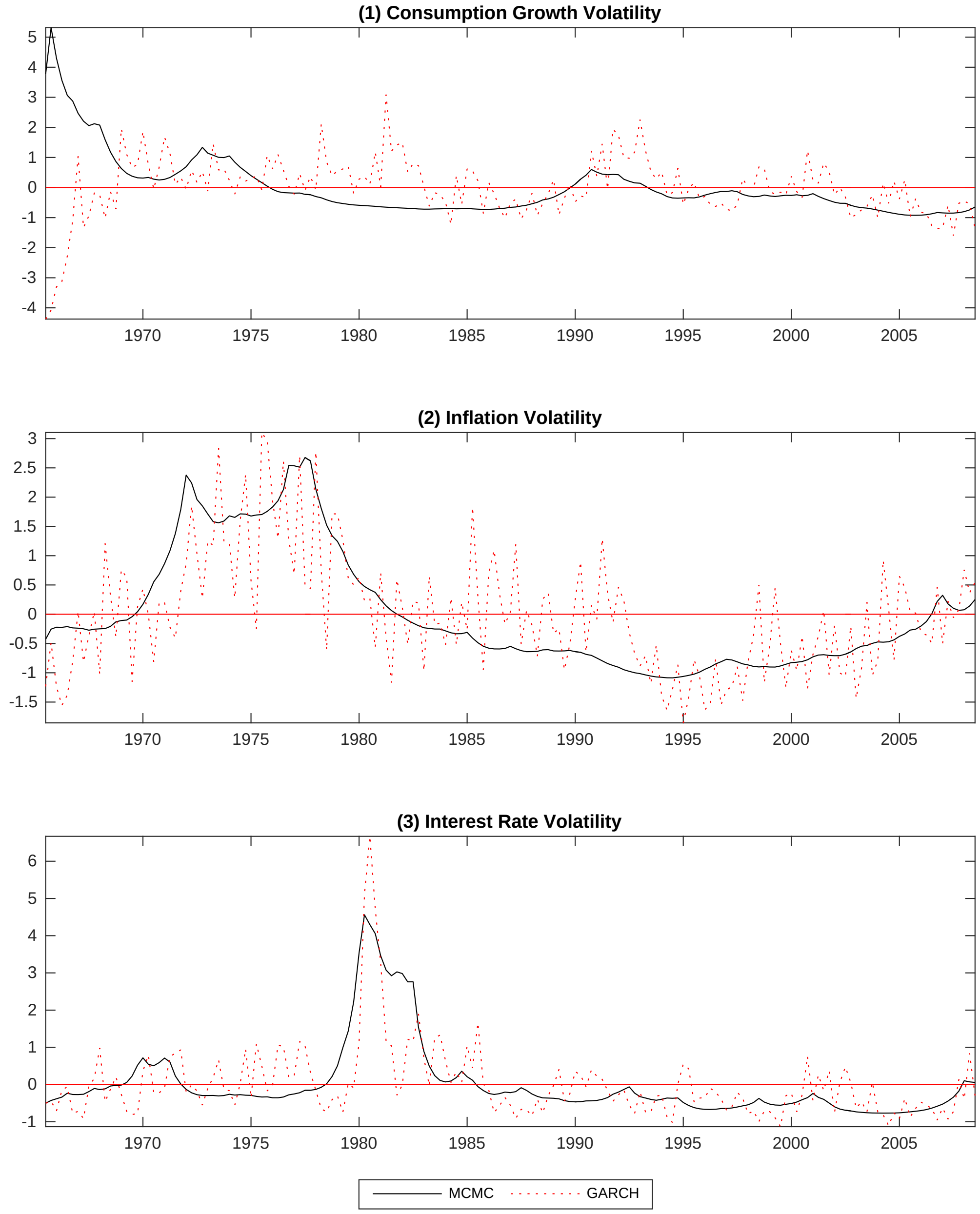

Figure I.4: MCMC filtered and GARCH estimated stochastic volatility series for consumption growth, inflation and the nominal short rate in the full sample from 1961Q3 to 2008Q3. All series are de-meaned and standardized. MCMC methodology follows Primiceri (2005) for the Time-Varying Parameter Vector Autoregression.

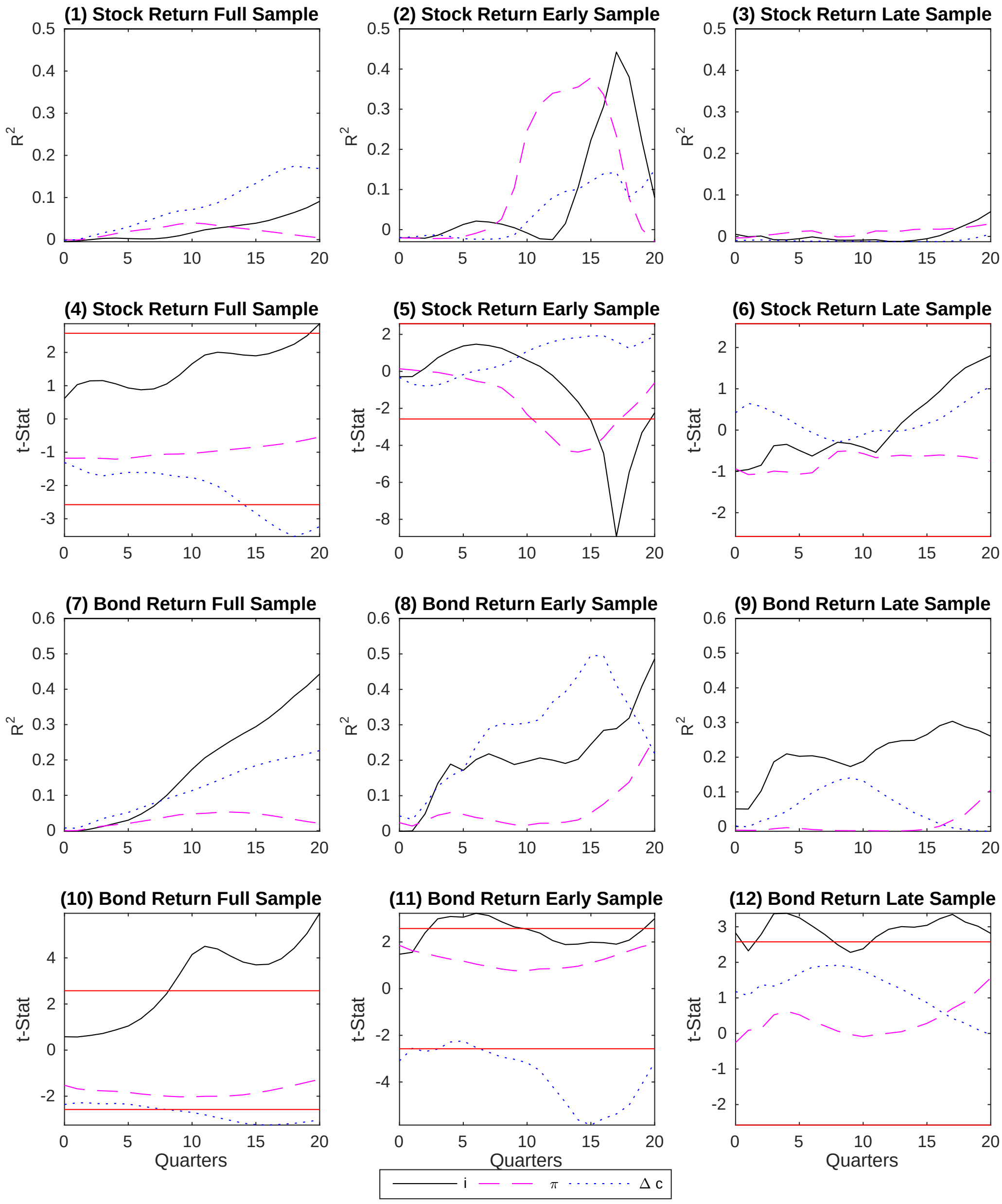

Figure I.5: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961Q3 to 2008Q3, the early sample from 1961Q3 to 1976Q4, and the late sample from 1982Q1 to 2008Q3. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first two rows) and nominal bonds (the bottom two rows). Univariate regressions in which the explanatory variables are volatilities of the nominal short rate (i), inflation (π) and consumption growth (Δc) are used. Odd rows report adjusted R^2, and even rows report coefficient t-statistics with 1% confidence interval bands. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Volatility construction employs MCMC, see Primiceri (2005).

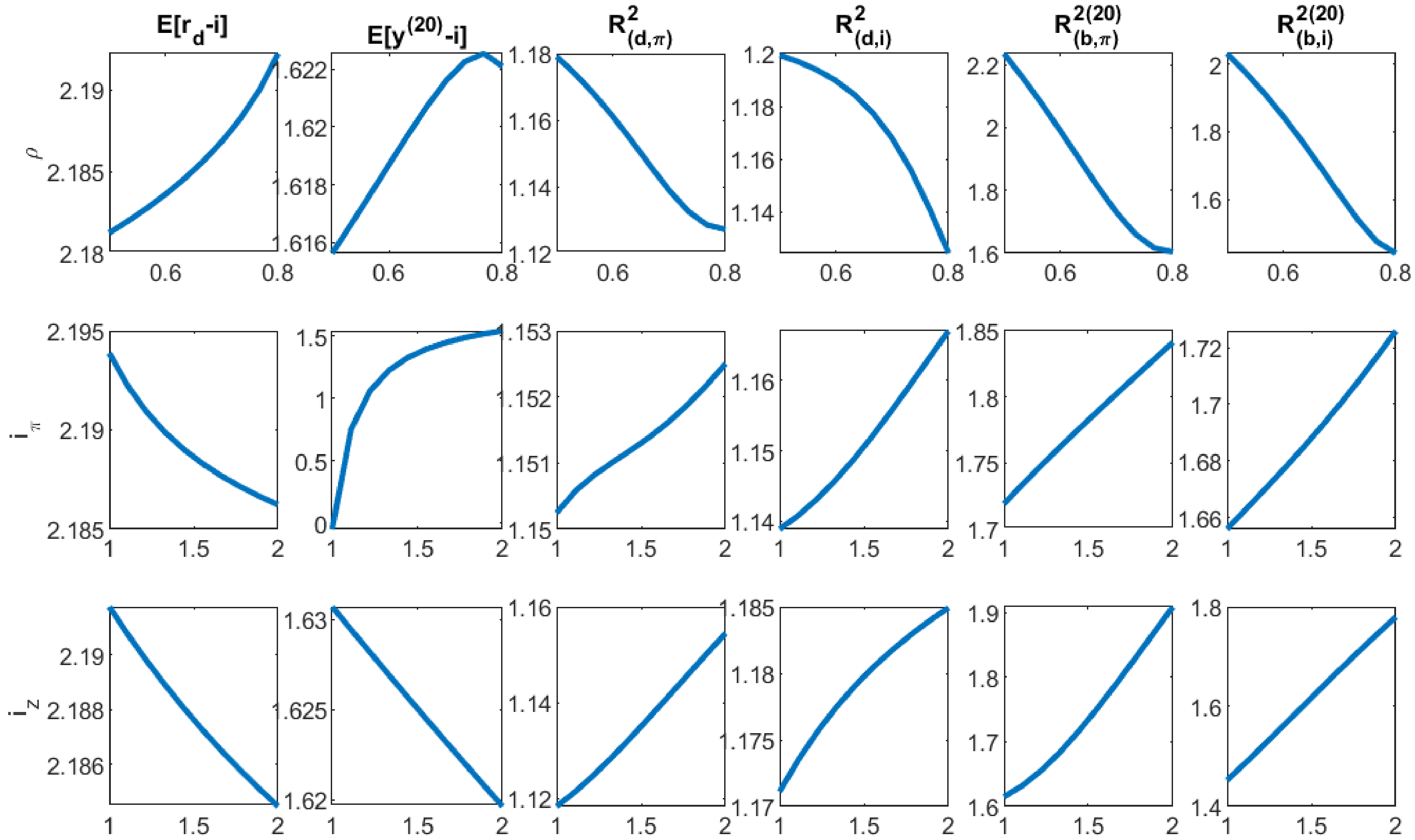

Figure I.6: Comparative statics for policy rule parameters. Top row for ρ, middle row for $\imath_\pi$, and bottom row for $\imath_z$. $E[r_d - i]$ denotes the average equity risk premium. $E[y^{(20)} - i]$ denotes the average 5-year nominal term spread. $R^2_{d,\pi}$, $R^2_{d,i}$, $R^2_{b,\pi}$, and $R^2_{b,i}$ are R^2s of predictive regressions for 20-quarter returns for stocks (d) or the 5-year bond (b) on the volatility of inflation (π) or the nominal short-term interest rate (i). Late sample calibration, 1982Q1 to 2008Q3. All values are in percentage terms.