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The Decline in Asset Return Predictability and Macroeconomic Volatility

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

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Abstract

We document strong U.S. stock and bond return predictability from several macroeconomic volatility series before 1982, and a significant decline in this predictability during the Great Moderation. These findings are robust to alternative empirical specifications and out-of-sample tests. We explore the predictability decline using a model that incorporates monetary policy and shocks with time-varying volatility. The decline is consistent with changes in both policy and shock dynamics. While an increase in the response to inflation in the interest-rate policy rule decreases volatility, more persistent and less volatile shocks explain the lower predictability.

JEL classification: E44, G12, G18.

Keywords: Asset return predictability, time-varying macroeconomic volatility, monetary policy, Great Moderation.

[*]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.

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1 Introduction

A large number of financial and macroeconomic variables have economically and statistically significant power to forecast stock and bond returns in predictive regressions.[1] The strength of the regression results, however, tends to depend on the sample period, which raises questions on both the robustness and the economic drivers of this predictability. In some equilibrium models, asset return predictability naturally arises from time-varying macroeconomic volatility that generates time-varying expected excess returns.[2] For instance, expected excess returns on financial assets in consumption-based asset pricing models depend on the volatility of consumption growth. Changes in this volatility are reflected in changes in compensation for risk in financial assets and, as a result, factors driving consumption growth volatility have predictive power for asset returns. It follows that the widely documented structural decline in the volatility of several macroeconomic variables around the early 1980s, often called the Great Moderation, may have affected the predictability of asset returns. More interestingly, the nature of these changes in predictability can shed additional light into the economic drivers of the volatility decline. In this paper, we study whether the observed reduction in macroeconomic volatility was accompanied by changes in asset return predictability, and use an economic model to explore whether changes in monetary policy or shock dynamics can explain the empirical findings.

In our empirical analysis, we verify the existence of a structural break in the volatility of several macroeconomic series during the first half of the 1980s. We find that the structural break does not only apply to the unconditional means of the volatility series, as found in

[1]See Fama and French (1988), Campbell and Shiller (1988*b*,*a*), Cochrane (1992), Lewellen (2004), Cochrane (2011), and Shiller (2014), among others.

[2]Alternatively, return predictability also can be obtained in models with time-varying prices of risk, such as in Campbell and Cochrane (1999). The focus of this paper, however, is the channel of time-varying macroeconomic volatility for predictability.

previous studies, but also to the volatility of these series. We then compare statistics from predictive regressions of stock and bond returns on well-known predictors and macroeconomic volatility, and find a significant decline in the predictive power of these variables. Based on these empirical findings, we develop an equilibrium model to learn whether the joint changes in macroeconomic volatility and asset return predictability can be explained by changes in an interest-rate policy rule, changes in the dynamics of fundamental shocks, or both. We find that an increase in the response to inflation in the policy rule can explain the decline in macroeconomic volatility; however, it cannot explain the reduction in return predictability, which is consistent with more persistent cost-push shocks with reduced variation in their volatility.[3]

We conduct a battery of predictability analyses, including out-of-sample tests, for both stock and bond returns using post-war data and two associated subsample periods. Using data for the 1961-2008 period, we find strong evidence of a structural break in macroeconomic volatility between 1980 and 1984, consistent with the Stock and Watson (2003) of the Great Moderation.[4] We split the full sample into two subsamples using 1982 as the breakpoint. The predictors are standard financial variables and several macroeconomic volatility series. The volatility series are constructed for consumption growth, inflation, the output gap, and the nominal short rate using transformations of residuals from a 10-variable VAR.

We document two main empirical findings. First, the macroeconomic volatility se-

[3]Cost-push shocks, widely studied in the macroeconomic literature, are shocks such as unexpected fluctuations in market power in product markets, exchange rates, or government regulation and taxation which may translate into changes in product prices. A common example of supply shocks is oil price shocks, given their widespread effect in the cost of production factors.

[4]Building on their conclusion that the structural break stems from the change in conditional volatilities rather than in conditional means, we apply a time-varying autoregressive model to the volatility series of 10 macroeconomic variables to test for potential breaks in both conditional means and volatilities of these series. The evidence points to a structural break in macroeconomic volatility more likely resulting from a change in the conditional volatility of volatility (vol-of-vol) than from a change in the conditional mean of volatility. Model-free tests of the volatility series also exhibit breaks around the same period.

ries, particularly those constructed from consumption growth and inflation, exhibit strong predictive power in explaining future stock and bond returns in the early subsample before 1982. In univariate regressions where future returns are regressed on current realized volatility, stock return predictability can be shown to achieve at least 10% R^2 with statistically significant coefficient loading at the 5% level around the 10-quarter holding period horizon and beyond; while bond return predictability can achieve those thresholds at the 4-quarter holding period horizon and beyond. The maximal R^2 across holding period horizons is 40% for stock returns, and roughly 60% for bond returns. The statistical significance on the estimated volatility coefficients survive when known stock and bond return predictors are also included, as well as when the standard errors of the estimated volatility coefficients are bootstrapped.

Second, return predictability for both equity and bonds declined significantly in the 1982-2008 sample period, after the structural break in macroeconomic volatility. When standard financial predictors are used, the maximal R^2 of equity return predictive regressions across prediction horizons dramatically decline in the late sample period (post-1982) with loadings turning from highly significant to insignificant. When macroeconomic volatilities are used as predictors, the maximal R^2 of equity return predictive regressions across prediction horizons drops from close to 40% in the early sample to less than 8% in the late sample. Bond return predictability shows a similar decline, from 60% to 25%. Statistical in- and out-of-sample tests imply larger residuals for the predictive regressions in the late sample than in the early sample.

We develop and calibrate an equilibrium asset pricing model for stocks and nominal bonds to learn about potential economic drivers of the documented decline in asset return predictability. The model builds on the long-run risk framework of Bansal and Yaron (2004) and extends it by adding a monetary policy interest-rate rule, a link between inflation and the real economy, and multiple sources of shocks with time-varying volatility. As a result, consumption growth and inflation endogenously depend on the policy rule and exhibit time-varying volatility. This allows us to conduct experiments involving changes in policy and shock parameters to learn whether they can explain a decline in asset return predictability.

The model is calibrated to match the return predictability and selected macroeconomic moments for the 1961-1976 period. Based on this calibration, policy and shock parameters are changed in the experiments to match the same moments for the 1982-2008 period. Consistent with the literature, an increase in the response to inflation in the policy rule decreases macroeconomic volatility. However, this increase does not produce a significant decline in asset return predictability, and points to simultaneous changes in shock dynamics to explain this decline. Among the three analyzed shocks, i.e, shocks to the natural rate of consumption growth, monetary policy shocks, and cost-push shocks, only a change in the dynamics of cost-push shocks results in reduced asset return predictability.

More persistent cost-push shocks with lower variation in volatility reduce the power of macroeconomic volatility to predict asset returns. Increased persistence in cost-push shocks amplifies the response of consumption growth, inflation, and their volatilities to these shocks. On the other hand, reduced variation in the volatility of cost-push shocks decreases the response of these variables to volatility shocks. As a result, asset returns become more sensitive to cost-push shocks and less sensitive to volatility shocks, respectively. This translates into a lower covariance between future asset returns and current macroeconomic volatility, decreasing the return predictive ability of this volatility. Empirically, we find that cost-push shocks during the 1982-2008 period are more persistent and less volatile, providing support to this channel for the predictability decline.

This paper is related to the literature on asset return predictability, macroeconomic volatility, and asset pricing with monetary policy. Koijen and Nieuwerburgh (2011) provide an extensive review of the return predictability literature. They summarize evidence not only on the predictive power of both financial and macroeconomic variables, but also on the instability of this power across sample periods. Schwert (1990), Lettau and Ludvigson (2001), Cooper and Priestley (2009), and Chava, Gallmeyer and Park (2015) show that variables such as the short-term interest rate, the consumption-wealth ratio, the output gap, and credit conditions, respectively, have significant predictive ability for asset returns. The unstable nature of this ability is highlighted by Ang and Bekaert (2007), Goyal and Welch (2003), Goyal and Welch (2008), and Lettau and van Nieuwerburgh (2008), among others. We show that several series of macroeconomic volatility predict bond and stock returns, but the significance of this predictability declined after the early 1980s.

Time-varying volatility in macroeconomic variables has been studied at least since the work of Engle (1982) on inflation. Both low- and high-frequency variations in macroeconomic volatility have been found in the data. Bloom (2009) highlights the importance of time variation in volatility to understand economic dynamics. In the asset pricing context, Bansal, Khatchatrian and Yaron (2005), Boguth and Kuehn (2013), Bansal, Kiku, Shaliastovich and Yaron (2014), and Tdongap (2015) find that the conditional volatility of consumption growth covaries with aggregate and cross-sectional stock returns, while Bansal and Shaliastovich (2012) provide similar findings for bond returns. Importantly, Kim and Nelson (1999), Perez-Quiros and McConnell (2000), and Stock and Watson (2003) find a structural decline in the early 1980s of the mean in the conditional volatility of a wide range of macroeconomic variables, labeled as the Great Moderation. Lettau, Ludvigson and Wachter (2008) use the decline in consumption volatility to explain a reduction in the equity premium. We complement the study of macroeconomic volatility by showing that the Great Moderation and lower expected asset returns were accompanied by a decline in the volatility of the conditional volatility of several macroeconomic variables, and by a significant reduction in the ability of this conditional volatility to predict asset returns.

Different explanations have been explored for the Great Moderation that include changes in monetary policy and reduced volatility in fundamental shocks. Most of this literature, however, focuses on macroeconomic dynamics with no clear implications for asset returns. Empirical studies such as Thorbecke (1997), Patelis (1997), Ehrmann and Fratzscher (2004), Bernanke and Kuttner (2005), and Chava and Hsu (2015) find a significant link between monetary policy and stock returns. However, they do not explore changes in this link over time. Palomino (2012), and Campbell, Pflueger and Viceira (2016) use New Keynesian models to understand how changes in policy credibility and a policy interest-rate rule, respectively, affect bond returns. Song (2016) explores the effect of monetary policy regimes on bond risk premia. We add to this literature by exploring a quantitative model with stochastic volatility in several shocks where a monetary policy rule affects bond and stock valuations. We use this model to analyze the effects on return predictability and macroeconomic variables of changes in the policy rule and shock volatility dynamics. This analysis provides additional asset return restrictions to identify the drivers of the Great Moderation.

2 Return Predictability and Macroeconomic Volatility

This section documents the power of different U.S. macroeconomic volatility series to predict aggregate stock and bond returns before 1980, which considerably declined during the Great Moderation. We first describe the construction of the macroeconomic volatility series, followed by an analysis of asset return predictability regressions using the obtained volatility series as predictors. To test for changes in this predictability over time, the analysis relies on structural break tests. Consistent with previous findings, there is a significant reduction in average macroeconomic volatility around the early 1980s. More importantly, this reduction was accompanied by a similar decline in the volatility of macroeconomic volatility (vol-of-vol), as well as in the ability of these series to predict asset returns. For robustness, we perform out-of-sample forecasts with "real time" estimation of macroeconomic volatility.

2.1 Data

We use quarterly data of U.S. macroeconomic and financial variables from 1961 to 2008. All macroeconomic series (described below) are from the FRED Economic database. All variables are real, deflated by the implicit GDP deflator, except for inflation and the nominal short rate. The output gap is defined as the HP-filtered deviation of output from a trend, at quarterly frequency. Government spending is Federal defense investment plus Federal non-defense investment plus state and local investment plus state and local consumption. Government revenue is Federal receipts plus state and local receipts minus net transfer minus net interest.[5] Stock return and dividend data are for the market portfolio from the Center for Research in Security Prices (CRSP).[6] Nominal bond yields, available at the Board of Governors of the Federal Reserve System website, are zero coupon yields following the procedure in Gurkaynak, Sack and Wright (2006).[7]

[5]U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Real Output [OUTNFB], Federal Government: Current Expenditures [FGEXPND], and Government Current Receipts [FGRECPT], retrieved from FRED, Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org/series/`, accessed March, 2017.

[6]Center for Research in Security Prices (CRSP), CRSP 1925 US Stock Database, Wharton Research Data Services (WRDS), `wrds-web.wharton.upenn.edu/wrds/about/databaselist.cfm`, accessed March, 2017.

[7]Board of Governors of the Federal Reserve System, `https://www.federalreserve.gov/econresdata/researchdata/feds200628.xls`, accessed March, 2017.

To motivate the subsample analysis, Table 1 presents summary statistics for different variables and sample periods. The variables are consumption growth, inflation, the nominal short-term interest rate, the output gap, aggregate dividend growth, and stock and bond returns. The sample periods are 1961QIII to 2008QIII (full sample) in Panel A, 1961QIII to 1976QIV (early sample) in Panel B, and 1982QI to 2008QIII (late sample) in Panel C. The selection of the early and late sample periods is described in section 2.3. Several well-documented changes in the properties of U.S. macroeconomic and financial variables are summarized in the table. In the late sample, the volatilities of consumption growth, inflation, and the output gap are lower, the volatility of the nominal short-term rate is higher, and the autocorrelations of inflation and the nominal short-term rate are lower and higher, respectively. In addition, there is a striking increase in the average excess returns of both stocks and bonds going from the early to the late samples: average stock returns increased from 1.64% to 2.83% per quarter, and average 5-year bond returns increased from 1.27% to 2.31%. With respect to joint dynamics, the correlation between consumption growth and inflation changed from strongly negative, −0.41%, to weakly negative, −0.08%, while the correlation between consumption growth and the nominal short-term rate switched from negative, −0.34%, to positive, 0.28%. Finally, the correlation between consumption growth and the excess return on the 5-year bond turned negative, −0.14%, in the second sample. This evidence is complemented with a joint econometric analysis of macroeconomic volatility and return predictability over time.

2.2 Macroeconomic Volatility

We use a vector autoregressive (VAR) approach to construct macroeconomic volatility series for the analysis of return predictability. We employ a 10-element VAR where the variables are output growth, consumption growth, hours growth, wage growth, investment growth, government spending growth, government revenue growth, inflation, output gap, and the effective Federal Funds rate. Specifically, the VAR is

$$\begin{bmatrix} \Delta ln(Output) \\ \Delta ln(Consumption) \\ \Delta ln(Hours) \\ \Delta ln(Wage) \\ \Delta ln(Investment) \\ \Delta ln(Spending) \\ \Delta ln(Revenue) \\ Inflation \\ OutputGap \\ FedFundsRate \end{bmatrix}_t = \alpha + B(L) \begin{bmatrix} \Delta ln(Output) \\ \Delta ln(Consumption) \\ \Delta ln(Hours) \\ \Delta ln(Wage) \\ \Delta ln(Investment) \\ \Delta ln(Spending) \\ \Delta ln(Revenue) \\ Inflation \\ OutputGap \\ FedFundsRate \end{bmatrix}_{t-1} + \varepsilon_t,$$

where $B(L)$ is the transition matrix with lags, and ε_t are the residuals that are transformed into volatilities. The volatility construction depends then 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 and squared errors are obtained by specifying volatility processes $\nu_{1,t}$ and $\nu_{2,t}$, respectively, that follow

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

for $k = \{1, 2\}$, where R and S are maximal lags used in the estimation. We choose $R = S = 5$ quarters. The estimation of these processes is performed using maximum likelihood assuming Gaussian distributed errors.

For our benchmark analysis, we jointly select the number of lags in the VAR and the volatility transformation based on two exercises.[8] First, we use daily data on the effective Federal Funds interest rate to calculate interest rate volatility at quarterly frequency. This volatility is compared with the volatility transformations for the same rate from VAR specifications with different lags. Second, we run full sample predictive regressions for stock and bond returns on each of the four volatility transformations for different number of VAR lags to compare their predictive ability. We choose the number of VAR lags and the volatility transformation that overall maximize the correlation of the implied interest-rate volatility with that constructed from daily data in the first exercise, and the predictive ability of the implied volatility for asset returns in the second exercise.

Table 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, for all four volatility transformations, 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 transformations.

[8] The VAR information criteria are ambiguous on which lag is appropriate, since AIC points to a VAR(4) structure while BIC points to a VAR(2). We use alternative lags and volatility transformations for comparison and robustness.

Next, we turn to predictive regressions of stock and bond returns using the full sample. The regression is

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

where $r^k_{t\to t+p}$ is the cumulative return from time t to time $t+p$ of asset $k = \{\text{stock, 5-year bond}\}$, and SV^j_t is one of the four volatility transformations for macroeconomic variable $j \in \{i, \pi, z, \Delta c\}$.[9] We focus on the volatility of the short-term interest rate (i), inflation (π), the output gap (z), and consumption growth (Δc). The first three variables are standard inputs in interest-rate policy rules, and consumption growth is an important driver of the stochastic discount factor in asset pricing models.

Figures 1 and 2 plot the R^2s of the predictive regressions of stock and 5-year nominal bond returns, respectively, under 12 different volatility constructions. In each figure, each of the three columns refers to regressions that use macroeconomic volatilities generated from residuals in VAR specifications with 1, 2, and 4 lags, respectively. Similarly, each of the four rows refers to regressions using absolute error, squared error, GARCH absolute error, and GARCH squared error, respectively, as volatility transformations. Three findings are important to highlight from the figures. First, as the number of lags in the VAR increases, the predictive power of i, π, z remains relatively stable for stock returns and decreases for bond returns. Second, the predictive power of the volatility of consumption growth for both stock and bond returns from a VAR(4) is higher than from a VAR(1). Finally, GARCH estimated volatilities outperform absolute and squared error of the residuals in predictive power.

Given the results from the two exercises above, we choose for the benchmark analysis a VAR(4) to obtain residuals, and a GARCH absolute error transformation of these residuals

[9] The cumulative bond return is the accumulated one-quarter returns of a bond with an initial maturity of 5 years each quarter.

to construct macroeconomic volatilities.[10] Table 3 reports coefficients on lagged variables from the baseline VAR estimation. Figure 3 plots the obtained volatility series for consumption growth, inflation, the output gap, and the Federal funds rate. All four series are positively correlated, and increase during recessions, consistent with the evidence in the literature.

2.3 Structural Break Tests of Macroeconomic Volatility

We use two structural break tests to detect cutoff time points for changes in macroeconomic volatility dynamics. We apply these tests to the volatility series estimated in Section 2.2, and the volatility of these series (vol-of-vol). The tests are the heteroscedasticity-robust Quandt (1960) likelihood ratio test (QLR) used by Stock and Watson (2003), and the CUSUM test developed in Page (1954). The results of these analyses are used in Section 2.4 to compare asset return predictability under different macroeconomic volatility environments.

Stock and Watson (2003) estimate time-varying autoregressive models on 168 macroeconomic series to analyze potential changes in the conditional mean (autoregressive coefficient) and/or the conditional variance in these models. They conclude that the Great Moderation decline in volatility is characterized by a sharp reduction in the conditional variance of GDP growth centered around 1982QIV to 1985QIII. We apply a similar procedure to find break points in the conditional mean and variance of the macroeconomic volatility series from Section 2.2. Specifically, the steps are:

- We estimate the AR(1) model of each of the 10 volatility series (indexed by j) with

[10] A VAR(2) or a GARCH squared error transformation for volatilities does not significantly alter the main empirical findings. The results of alternative specifications are available upon request.

time-varying coefficients:

$$SV_t^j = \alpha_t^j + \rho_t SV_{t-1}^j + \nu_t^j,$$

where the conditional mean $\alpha_t + \rho_t SV_{t-1}^j$ has a potential break at $t = \kappa_j$, and the conditional variance $var_t(\nu_{t+1}^j)$ has a potential break at $t = \tau_j$.

- We maximize the Chow test F statistic over the central 70% of the sample to find the conditional mean break point κ_j.
- To find the break point of the conditional vol-of-vol, τ_j, we estimate the AR(1) model without any breaks and obtain the residuals. The absolute value of these residuals are regressed on a constant and a binary variable, where the binary variable is 0 for $t < \tau_j$, and 1 for $t \geq \tau_j$. The QLR statistic is the squared t statistics of the binary variable. We search over the central 70% of the sample for the maximal QLR statistic to determine τ_j.

The estimated potential break points for the conditional mean and variance of the macroeconomic volatility series are presented in Table 4. For comparison, structural break test results are reported for the four volatility transformations explored in Section 2.2. Odd columns are the estimated breaks in the conditional mean of the volatility series while even columns are the estimated breaks in the conditional variances. We focus on the break points in consumption growth, inflation, the output gap, and the Federal funds rate.

In general, the estimated break dates are more statistically significant for conditional variances than for conditional means, especially for the GARCH filtered models in columns (5) to (8) in Table 4. Columns (5) and (7) show that none of the break dates in the conditional mean is statistically significant with the exception of the Federal funds rate for the GARCH-SQR model. On the other hand, the estimated break dates in the conditional volatility are statically significant at the 5% level for the volatility series of consumption growth, inflation, and the output gap in columns (6) and (8). The evidence from the GARCH models suggests that the structural break associated with the Great Moderation is more likely attributed to a change in the conditional vol-of-vol, as opposed to a change in the conditional mean of macroeconomic volatility. Across the four volatility transformations, the estimated break dates for the conditional variance of consumption growth volatility range between 1969QIII and 1983QI. The estimated break dates for the conditional vol-of-vol on inflation and the output gap have a narrower range between 1977QI and 1984QII. Lastly, for interest rate volatility, the estimated break in conditional variance is 1985QIV, but insignificant for the GARCH models. Consistent with the finding of Stock and Watson (2003), the QLR statistics suggest the structural break in macroeconomic volatility is likely to have taken place between 1980QI and 1984QIV.

For robustness, we use a second test to determine break points in macroeconomic volatility. Figure 4 and Figure 5 plot results of a CUSUM test applied to each of the 10 macroeconomic volatility series, and the squared value of these series, respectively. CUSUM tests the null that there is no change in the mean of a given series without assuming any underlying distribution.[11] In each figure, the four subplots correspond to the four volatility transformations. In each subplot, the vertical-axis is the year of the potential break point, and the horizontal axis contains each of the 10 variables in the VAR. For the purpose of the return predictability analysis, we focus on the tests for consumption growth, inflation, output gap, and the Federal funds rate. A missing data point means the CUSUM test is not able to find a break point in the series.

[11] We do not use weight to adjust the cumulative sum in the max operator and use a threshold of 0.01 to be conservative.

Figure 4 shows that consumption growth and output gap volatilities exhibit breaks right around 1980, while, inflation volatility and interest rate volatility display breaks in the early part of 1980. Figure 5 shows that the CUSUM test finds similar breaks in the vol-of-vol for consumption growth and inflation when the volatilities are constructed using GARCH estimations (subplots (c) and (d)). The vol-of-vol of consumption growth, inflation, the output gap, and the short rate exhibit break points around 1980, consistent with the results from the QLR test.

2.4 Return Predictability

Based on the structural break evidence for macroeconomic volatility, we conduct stock and bond return predictive regressions for post-war data before and after the structural break. The early sample is from 1961QIII to 1976QIV, and the late sample is from 1982QI to 2008QIII. The gap between the two subsamples eliminates the policy experiment period as well as the Oil Shock, which has an outsized influence on return predictability, as shown by Goyal and Welch (2008). The predictability analysis is performed using standard predictors and macroeconomic volatility. For each set of predictors, we conduct predictive regressions for stock and bond cumulative returns with horizons from 1 to 20 quarters. All t-statistics are calculated from GMM-corrected standard errors incorporating Newey-West weighting and 10 lags.

2.4.1 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.[12] This analysis is useful to make comparisons to the predictive ability of macroeconomic volatility.

The regressions are

$$r^k_{t\to t+p} = \alpha^k_p + \beta^k_{p,j} Pred^k_t + \varepsilon^k_{j,t+p}, \tag{2}$$

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 $j = \{d-p, cay, f\}$.

Figures 6, 7, and 8 show statistics of predictive regressions for the full, early, and late samples. Subplots in the left column are for R^2s of the regressions, and subplots in the right column are for t-statistics. The horizontal axes denotes the horizon of cumulative returns in quarters. The three rows contain results for regressions of stock returns on dividend yields, stock returns on cay, and bond returns on forward rates, respectively.

For the full sample 1961QIII to 2008QIII in Figure 6, the top row shows that the R^2s of the predictive regressions on the dividend yield are substantial at long return horizons, with significant slope coefficients beyond 2-quarter holding period horizons. The results are similar when cay is used as the regressor to predict stock returns. The second row in the figure indicates that the maximal R^2 is about 25% at 14 quarters, and the estimated slope coefficients are statistically significant for almost all return horizons. For 5-year bond returns, the third row in the figure shows that forward rates have monotonically increasing predictive power at longer horizons. However, the slope coefficients are generally

[12] We choose to use individual forward rates as opposed to the Cochrane and Piazzesi (2005) factor because their estimated coefficients are for monthly observations whereas we are using quarterly observations. Furthermore, 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.

insignificant at the 5% level beyond 4 quarters.

Figure 7 presents the results for the predictive regressions in the early sample 1961QIII to 1976QIV. In the top row, dividend yield has 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. The same is true for *cay* in predicting stock returns in the second row of the figure: a maximal R^2 of around 40% at the 12 quarter horizon with highly significant estimated slope coefficients in the medium horizon. For bond returns in the bottom row, 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.

Figure 8 summarizes the predictive regression results for the late sample 1982QI to 2008QIII. In general, the evidence of predictable stock and bond returns is weaker relative to the early sample. For stock returns, in the top and middle rows, 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 in the top row, the maximal R^2 is around 40% compared with more than 50% in the top row of Figure 7. The statistical significance of the slope coefficients on both dividend yield and *cay* considerably declines. In fact, estimated coefficients on *cay* are only significant at the very short and the very long cumulative return horizons, and they are insignificant between 5- and 15-quarter holding periods. For bond return regressions on forwards rates, results in the bottom row 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.

2.4.2 Macroeconomic Volatility as Predictor

We use the macroeconomic volatility series described in Section 2.2 to run the predictive regressions specified in equation (1). The dependent variables are stock and bond cumulative returns with horizon p from 1 to 20 quarters. We focus on the volatility of four macroeconomic variables: the nominal short-term rate, inflation, the output gap, and consumption growth, since they are standard variables in asset pricing models with monetary policy. Regressions on the volatility of the remaining six variables in the VAR are analyzed but not reported here. The predictive power of output growth volatility is similar to that of the output gap, while the volatilities of hours, wage, investment, government spending, and revenue growth rates do not outperform those of the selected four variables.

Figures 9, 10, and 11 show the predictive power of the macroeconomic volatility series in the full, early, and late samples. For each sample, residuals (and volatilities) are obtained from the VAR in Section 2.2 using only observations within the sample period. The respective left columns of the figures display the R^2s of the predictive regressions, and the right columns display the t-statistics of the estimated slope coefficients, $\beta^k_{p,j}$, in equation (1).[13] The first two rows shows results for stock and bond return regressions, respectively, on macroeconomic volatility. The bottom two rows are for similar regressions with added control variables in the form:

$$r^k_{t\to t+p} = \alpha^k_p + \beta^k_{p,j} SV^j_t + \eta^k_{p,j} Control_t + \varepsilon^k_{j,t+p}, \tag{3}$$

for $k = \{\text{stock, 5-year bond}\}$, where the controls are the dividend yield and the *cay* factor for stock return regressions, and forward rates for bond return regressions.

[13] To calculate the t-statistics for all the regressions in the empirical exercise, GMM estimated standard errors are used. For robustness, we repeat the exercise with Newey-West corrected standard errors and the results do not change.

For stock returns, Figure 9 for the full sample shows that the volatility of inflation dominates the volatility of the other three variables in predicting future returns at short horizons in terms of R^2, except for the very long horizon, beyond 18 quarters, where interest rate volatility has better explanatory power. In terms of t-statistics, none of the loadings on volatility is significant at any horizon in the top right subplot. However, when control variables are added to the regressions, the third subplot in the right column shows that interest rate volatility significantly predicts returns in the short-to-medium term, while the volatility of the output gap and consumption growth have significant loadings for longer horizons. Interestingly, the loading on interest rate volatility is significantly negative on 4- to 8-period returns, which implies that high interest rate volatility typically lead periods of low expected stock returns in the 1961QIII to 2008QIII sample.

For 5-year bond returns, the second subplot in the left column of Figure 9 indicates that interest rate volatility outperforms the other three volatilities in the predictive regressions beyond 6 quarters. For the shorter horizon holding period returns, consumption growth volatility dominates. However, once forward rates are included as controls in the regressions, the bottom left subplot shows that inflation volatility outperforms the rest when predicting bond returns in the medium to long horizon in terms of R^2. This is also reflected in the t-statistics in the bottom right plot: the estimated loading on inflation volatility is the only one consistently significant when holding period returns of 6 quarters or more are used in the regressions. Furthermore, this loading is negative, meaning that high inflation volatility lead to low future bond returns. Interest rate and consumption growth volatilities both have positive and significant coefficient loadings on bond returns in the medium to long horizon, as shown by the second subplot of the figure . However, once the forward rates are included in the regressions, the bottom subplot shows that inflation volatility is the only variable having a significant coefficient loading consistently across horizons.

Figure 10 reports regression results for the early sample 1961QIII to 1976QIV. The R^2s indicate that consumption growth and inflation volatilities are stronger predictors than interest rate and output gap volatilities for both stock and bond returns. Consumption growth volatility especially stands out in the long horizon beyond 15 quarters, reaching a maximum of roughly 40% for stocks and 70% for bonds in the top two subplots on the left. The bottom two left subplots in the figure confirm the predictive power of consumption growth and inflation volatilities in the longer horizon when control variables are added. With respect to the statistical significance of the estimated loadings on volatility displayed in the right column of the figure, the bottom two subplots show that, for long horizon predictive regressions at 15 quarter or more, the coefficient loadings on consumption growth and interest rate volatilities are highly significant for stock returns, while all four variables have significance for bond returns. Also, future stock and bond returns load with opposite signs on volatility. The third subplot in the right column indicates that loadings in long horizon stock return regressions are negative, whereas the bottom subplot show positive loadings for bond return regressions. That is, periods of high volatility are followed by low stock returns and high bond returns at long horizons during the period 1961QIII to 1976QIV. Furthermore, in both cases, the loadings on volatility switch signs: from positive in the short to medium horizon around 8 quarters to negative in the long horizon for stock returns, and from negative in the short horizon to positive in the long horizon for bond returns.

For the late sample 1982QI to 2008QIII, predictive regression results are shown in Figure 11. Overall, return predictability for stocks and bonds is significantly lower than for the early sample. In regressions on volatility with no control variables, the maximal R^2 for stock returns is about 8% (output gap volatility), and the maximal R^2 for bond returns is roughly 25% (inflation and output gap volatilities), both substantially lower than in the early period. From the top left subplot of the figure, consumption growth volatility does not predict stock returns. Once the dividend yield and *cay* are included as control variables, the third subplot in the left column shows that inflation volatility dominates the remaining three volatilities in terms of R^2 of the predictive regressions. For bond returns, in the second subplot in the left column, inflation and output gap volatilities generate the highest R^2s, and consumption growth volatility has no predictive power across all horizons. In addition, the right column shows statistical significance of the estimated volatility loadings in equations (1) and (3). For stock returns, the only significant loading is on inflation volatility at long horizons when the dividend yield and *cay* are included as control variables. For bond returns, the loading on inflation volatility becomes barely significant at the 5-year horizon once the forwards rates are used as controls. Figure 12 plots the t-statistics using bootstrapped standard errors[14] in univariate return predictability regressions when macroeconomic volatilities are the predictive variables. Each subplot shows the t-statistics across holding period return horizons. Comparison between the second and third rows of Figure 12 documents that the coefficient estimates in these predictability regressions are more statistically significant in the early sample (second row) relative to the late sample (third row), in line with our conclusion by examining R^2s in Figures 10 and 11.

For robustness, we perform hypothesis testing using unpaired t test and F test with the null that the residuals from predictive regressions for the early and late samples are similar in magnitude. Figures 13 and 14 plot the results for stock and bond returns, respectively. The subplots (a) to (d) in both figures correspond to the four volatility series used as

[14]For each sample period, after running the univariate predictive regression, we retain the fitted value and the residuals. Then, we sample the residuals, add back to the fitted values, and create synthetic returns. Finally, we reestimate the model using the synthetic returns and retain the coefficient estimates. Repeat the process 1000 times, and calculate the t values for each holding period return horizon and for each volatility predictor.

predictors: consumption growth, inflation, output gap, and the nominal short-term rate, respectively. The p-value of the tests are plotted against the horizon of cumulative returns. The red horizontal lines in each subplot of the figures indicate the 5% significance level. For stock returns, both the unpaired t test and the F test reject the null hypothesis at the 5% level for medium and long horizon predictive regressions beyond 10 quarters, except for subplot (c) where output gap volatility is the predictive variable. For bond returns, the null hypothesis is always rejected at all horizons and across all predictors, from (a) to (d). The t test and the F test provide statistical evidence that the fit of the predictive regressions is significantly better in the early sample, consistent with the higher R^2s in Figure 10 relative to Figure 11.

Overall, the subsample analysis highlights three properties of the link of asset returns and macroeconomic volatility in the data. First, the predictive power of macroeconomic volatility drops in the late sample relative to the early sample for both stock and bond returns. Second, among macroeconomic volatilities, consumption growth and inflation volatilities have the largest predictive power for asset returns in the early and late samples, respectively. Third, consistent across both sample periods, long horizon stock and bond returns load negatively and positively, respectively on lagged volatility.

2.4.3 Out of Sample Evidence on Return Predictability

The empirical asset pricing literature has popularized in recent years the use of out of sample forecasts as a more stringent test on the predictive power of explanatory variables. Out of sample forecasts serve as a natural way to compare the predictive power of macroeconomic volatility across subsamples. If the early sample (1961QIII to 1976QIV) exhibits stronger stock and bond return predictability from macroeconomic volatility relative to the late sample (1982QI to 2008QIII), the root mean square errors of the forecast deviation from realized returns should be smaller. We conduct this analysis in this section.

To examine the out of sample performance of macroeconomic volatilities on returns, we implement the following strategy in "real time." First, within each sample, we use the first half of observations to form the initial estimation window. The benchmark 10-vector VAR is implemented within the window to find the residuals of consumption growth, inflation, output gap, and the nominal short rate.[15] As in the benchmark analysis, volatilities are calculated by applying a GARCH absolute error transformation to these residuals. 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. The procedure is repeated by expanding the estimation window each quarter. The maximal estimation window is the length of the sample minus the holding period horizon of the forecast. Finally, we calculate root mean square errors (RMSE) implied by the forecasts relative to realized returns.

The resulting RMSEs for the full, early, and late samples are summarized in Table 5. Panels A, B, and C report the RMSEs 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 all four macroeconomic volatility series. When the volatility of consumption growth is used to forecast 16-quarter stock returns (Panel B, column 1), the average forecast error in the early and late sample are 0.29%, and 0.39%, respectively. For bond returns, column 2 shows that the average forecast error using consumption growth volatility as the predictor is smaller for the early sample

[15]For the out of sample test, we use a VAR(2) instead of a VAR(4) limited by the number of observations we have in the early subsample.

($\sim$ 13%) relative to the late sample ($\sim$ 17%). A similar pattern emerges for the other macroeconomic volatility variables. For example, inflation volatility generates a stock return predictability RMSE of about 22% in the early sample compared with 40% in the late sample, and a bond return predictability RMSE of about 13% in the early sample compared with 17% in the late sample. The only instance in Table 5 where the RMSE is not smaller in the late sample relative to the early sample is in column 2 of Panel C. When the output gap and interest rate volatilities are used to predict 20-quarter holding period bond returns, there is a small decline in RMSEs from the early sample to the late sample. In summary, the out of sample forecast exercise solidifies our main empirical finding using predictive regressions: both stock and bond returns across holding period horizons are less predictable in the post-1982 sample using macroeconomic volatilities.

3 Equilibrium Model

We build an equilibrium model to learn about potential economic channels driving the documented decline in return predictability in recent years. The model is an extended version of the long-run risk (LRR) Bansal and Yaron (2004) model, adding an endogenous process for inflation to price nominal bonds. The model incorporates an interest-rate policy rule, multiple sources of shocks with time-varying volatility, and an equation linking inflation and the real economy. This setting allows us to obtain an inflation process and a component of consumption that depend on monetary policy, while preserving most of the endowment economy structure of the standard long-run risk model. Kung (2015) uses a similar framework in a production economy setting to analyze the term structure of interest rates. The model is calibrated to U.S. data and several experiments are conducted to understand the effect of monetary policy and volatility dynamics on asset return predictability.

3.1 Economic Environment

The representative household has recursive preferences on consumption, C_t, and has access to real and nominal financial claims in a complete market. The relevant equilibrium conditions are:

$$M_{t,t+1} = \left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right]^{\theta}\left(\frac{1}{R_{c,t+1}}\right)^{1-\theta}, \tag{4}$$

$$e^{-i_t} = \mathbb{E}_t\left[M_{t,t+1}e^{-\pi_{t+1}}\right], \tag{5}$$

$$1 = \mathbb{E}_t[M_{t,t+1}R_{c,t+1}], \tag{6}$$

$$\Delta c_t = \Delta c_t^f + \Delta z_t, \tag{7}$$

$$\pi_t = a_\pi + \phi_{\pi z}\Delta z_t + \beta_\pi \mathbb{E}_t[\pi_{t+1}] + \epsilon_t, \tag{8}$$

$$i_t = \bar{\imath} + \imath_\pi \pi_t + \imath_z \Delta z_t + u_t. \tag{9}$$

Equation (4) characterizes the one-period real pricing kernel, $M_{t,t+1}$, in terms of consumption and the return on the consumption claim, $R_{c,t}$. The parameter ψ captures the elasticity of intertemporal substitution of consumption (EIS), and $\theta \equiv \frac{1-\gamma}{1-1/\psi}$ captures the effects of differences between the risk aversion coefficient, γ, and the inverse of EIS. Equation (5) provides the price of a one-period nominal bond, with implied one-period nominal interest rate, i_t, where inflation is π_t. This interest rate is also the instrument of monetary policy. Equation (6) is the pricing equation for the consumption claim. Equation (7) describes consumption growth, $\Delta c_t \equiv \log C_t - \log C_{t-1}$, in terms of two components. First, c^f, which is interpreted as the component of consumption that is not affected by monetary policy. For instance, this can be the natural rate of consumption in an economy with no nominal rigidities. Second, z_t, which is interpreted as the component of consumption that is affected by monetary policy. For simplicity, we refer to c_t^f and z_t as the "natural rate of consumption" and the "output gap," respectively. Equation (8) characterizes the link between inflation and the output gap, where ϵ_t is a cost-push shock. This equation can be derived from a model with price rigidities as in Woodford (2003).[16] Equation (9) is the interest-rate policy rule where the nominal interest rate is set depending on inflation, changes in the output gap, and policy shocks u_t.

Risk in the economy is captured by innovations to the natural rate of consumption growth and its conditional mean, $\varepsilon_{c,t}$, and $\varepsilon_{x,t}$, respectively, monetary policy shocks, $\varepsilon_{u,t}$, cost-push shocks, $\varepsilon_{\epsilon,t}$, and shocks to volatility, $\varepsilon_{v,t}$. Specifically,

$$\begin{aligned} \Delta c_{t+1}^f &= \mu_c + x_t + \sigma_{c,t}\varepsilon_{c,t+1}, \\ x_{t+1} &= \phi_x x_t + \sigma_{x,t}\varepsilon_{x,t+1}, \\ u_{t+1} &= \phi_u u_t + \sigma_{u,t}\varepsilon_{u,t+1}, \\ \epsilon_{t+1} &= \phi_\epsilon \epsilon_t + \sigma_{\epsilon,t}\varepsilon_{\epsilon,t+1}, \\ v_{t+1} &= \phi_v v_t + \sigma_v \varepsilon_{v,t+1}, \end{aligned} \tag{10}$$

where conditional variances follow the process

$$\sigma_{k,t}^2 = \bar{\sigma}_k^2 + \sigma_{kv} v_t, \tag{11}$$

for $k = \{c, x, u, \epsilon\}$, and $\varepsilon_{k,t} \sim \text{IID}\mathcal{N}(0,1)$.

The appendix shows that equilibrium implies solutions for the change in the output

[16] For simplicity, we characterize a link between inflation and changes in the output gap, instead of the output gap level. This particular specification, where inflation depends also on the lagged output gap level, can result from a model with habit formation on consumption preferences.

gap and inflation given by

$$\Delta z_t \;=\; z_x x_t + z_u u_t + z_\epsilon \epsilon_t + z_v v_t, \quad \text{and} \quad \pi_t = \bar{\pi} + \pi_x x_t + \pi_u u_t + \pi_\epsilon \epsilon_t + \pi_v v_t,$$

respectively.

3.2 Stock and Bond Returns

Stocks are a claim on dividends, d_t. Following the long-run risk literature, dividend growth is given by

$$\Delta d_{t+1} = \mu_c + \phi_{dc}\mathbb{E}_t[\Delta c_{t+1} - \mu_c] + \sigma_{dc}\sigma_{c,t}\varepsilon_{c,t+1} + \sigma_{d,t}\varepsilon_{d,t+1},$$

where $\sigma_{d,t}^2 = \bar{\sigma}_d^2 + \sigma_{dv} v_t$. Real stock returns, $R_{d,t}^r$, satisfy the pricing equation $1 = \mathbb{E}_t[M_{t,t+1}R_{d,t+1}^r]$. These returns can be written in terms of the log price-dividend ratio, $p_{d,t}$, and dividend growth as

$$\log R_{d,t+1}^r = \log\left(1 + e^{p_{d,t+1}}\right) + \Delta d_{t+1} - p_{d,t} \approx \bar{\eta}_d + \eta_d p_{d,t+1} + \Delta d_{t+1} - p_{d,t},$$

with approximation constants $\bar{\eta}_d$ and η_d defined in the appendix. For data comparisons, we define the nominal (log) stock return as

$$r_{d,t} = \log R_{d,t}^r + \pi_t.$$

The nominal yield of the n-period bond is $y_t^{(n)}$. The corresponding bond price satisfies the recursive equation

$$e^{-ny_t^{(n)}} = \mathbb{E}_t \left[M_{t,t+1} e^{-\pi_{t+1} - (n-1) y_{t+1}^{(n-1)}} \right],$$

and the nominal one-period bond return is

$$r_{t+1}^{(n)} = \log R_{t+1}^{(n)} = -(n-1) y_{t+1}^{(n-1)} + n y_t^{(n)}.$$

Equilibrium implies solutions for the price-dividend ratio and bond yields given by

$$\begin{aligned} p_{d,t} &= \bar{p_d} + p_{d,x} x_t + p_{d,u} u_t + p_{d,\epsilon} \epsilon_t + p_{d,v} v_t, \\ \text{and} \quad y_t^{(n)} &= \bar{y}^{(n)} + y_x^{(n)} x_t + y_u^{(n)} u_t + y_\epsilon^{(n)} \epsilon_t + y_v^{(n)} v_t, \end{aligned}$$

respectively, with coefficients reported in the appendix.

4 Analysis

In this section, we describe the calibration exercise and policy experiments meant to capture certain stylized facts in the data and learn about the economic mechanisms at work. Based on the model implications, we provide further empirical evidence that provides support to the mechanism capturing a reduction in asset return predictability.

4.1 Model Calibration

The model is calibrated to replicate properties of macroeconomic and financial U.S. quarterly data for the period 1961QIII to 1976QIV. The purpose of the calibration is to obtain a reasonable baseline model to explore, through quantitative experiments, whether the structural break in volatility dynamics and the documented changes in asset predictability around 1980 can be explained by changes in monetary policy, changes in the properties of fundamental shocks, or a combination of both. This approach is similar in spirit to the one in Campbell, Pflueger and Viceira (2016). The data description is presented in the empirical section. We assume that decisions in the model are made at quarterly frequency to use the closed-form solutions of model moments in the calibration. Standard long-run risk models are usually calibrated at annual frequency by aggregating monthly simulated data implied by the model. A disadvantage of this approach is that it requires model simulations to compute numerical moments, which considerably reduces the computational speed for calibration purposes. On the other hand, a limitation of our approach is the fact that closed-form moments for variables of interest such as the volatility of conditional volatility, and the statistics of predictive regressions on volatility are not available. We deal with this limitation as explained below.

The calibration consists in choosing a set of parameters that minimizes deviations of selected model moments from their data counterparts. As a first step, a constant volatility model is calibrated to obtain a reasonable set of initial values for all parameters, except for the loadings on the volatility process σ_{kv} for $k = \{x, u, \epsilon, d\}$, which are set to zero. The moments that are used in this step are the standard deviation and first-order autocorrelation of consumption growth, inflation, and the one-quarter nominal interest rate, as well as the paired correlations among these variables. The dividend growth process is calibrated to match the volatility of dividend growth and the correlation of consumption and dividend growth. In addition, the average inflation and one-quarter nominal interest rates, the average price-dividend ratio, the average equity premium, and the average 5-year nominal bond spread are targeted in the calibration.

The constant volatility model, by construction, implies that asset returns cannot be predicted by macroeconomic volatility, in contrast with the empirical findings. We use the calibration of the constant volatility model as a starting point to calibrate the model with time-varying volatility. In addition to the parameters calibrated for the model with constant volatility, parameter values for the loadings on volatility σ_{kv} for $k = \{x, u, \epsilon, d\}$ are also chosen. Ideally, in order to identify these parameters, we would use statistics from the predictive regressions of asset returns on macroeconomic volatility. Unfortunately, these statistics are not available in closed-form. We then target slope coefficients and R^2's of the alternative predictive regressions of 5-year cumulative returns of stocks and 5-year nominal bonds on the level of the variable. We also add the restriction that the equity premium and the bond spread have to be above certain level, to avoid calibrations with counterfactually low values for these moments. The minimization of moment deviations is performed multiple times from initial points that are perturbations from the parameter values of the model with constant volatility. For each reasonable minimization, we compute numerical moments of the predictive regressions of asset returns on macroeconomic variance and choose the parameter values with the best implications for these regressions. A VAR of the simulated macroeconomic variables is used to obtain conditional variances as the square of the VAR residuals.

Table 6 shows the parameter values for the calibration. The elasticity of intertemporal substitution above 1 is close to the value in Bansal and Yaron (2004). The coefficient of risk aversion is 30, which is higher than the values used in the long-run risk literature to match the equity premium. The higher value is needed to match the average bond spread. The coefficient $\phi_{\pi z}$, which captures the link between inflation and the real economy is negative in order to match the observed negative correlations of consumption growth with inflation and the nominal interest rate. The response in the policy rule to inflation, around 1.45, is close to the estimates found in the literature, and the response to changes in the output gap is negative, around -0.35. With respect to the shock parameters, the process x_t does not exhibit autocorrelation, and its loading on volatility is negative. Policy shocks have significant autocorrelation and a positive loading on volatility. Cost-push shocks are not autocorrelated and have a negative loading on volatility. Finally, the volatility process is highly autocorrelated.

Table 7 shows several moments implied by the calibration. The model calibration matches the volatility of the one-quarter nominal interest rate, and implies a consumption growth and inflation volatilities slightly higher and lower than in the data, respectively. The autocorrelations of inflation and the nominal interest rat, although lower lower than in the data, are significantly positive. The negative correlation between consumption growth and inflation is well captured, as well as the correlations of the nominal interest rate with consumption growth and inflation. The quarterly equity premium is 83 bps and the average bond spread is 77 bps, both similar to those implied by the data. The calibration does a reasonable job capturing the R^2s of the predictive regressions of the 5-year bond cumulative return on macroeconomic volatility. On the other hand, the R^2s for the comparable stock return regressions are lower than in the data. Overall, the calibration captures important aspects of the U.S. economy during the 1961-1976 period, and provides a reasonable baseline framework to conduct experiments and analyze their effects on asset return predictability.

4.2 Experiments

We use data for the subsample 1982QI - 2008QIII to learn whether the joint changes in macroeconomic volatility dynamics and return predictability observed during this period, relative to the subsample 1961QI - 1976QIV, can be explained by changes in policy parameters, properties of fundamental shocks, or both. Specifically, the experiments consist in changing selected parameters to match the moments targeted in the calibration for the 1982QI - 2008QIII subsample, while keeping the remaining parameters at their baseline levels.[17] 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 that was accompanied by an increase in the autocorrelation of the three-month nominal interest rate, 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 spread and higher average excess stock returns, and the reduction in the asset return predictability explained by macroeconomic volatility.

The experiments are divided into three groups: changes only to policy parameters, changes only to shock parameters, and changes to shock parameters accompanied by a stronger response to inflation in the policy rule.[18] For simplicity, policy parameters group the responses to inflation, $\imath_\pi$, and changes the output gap, $\imath_z$, in the monetary policy rule, as well as the coefficient linking inflation to the real economy, $\phi_{\pi z}$. This parameter can be affected by pricing policies in the production sector.

Table 8 reports the results of the experiments with changes to policy parameters. The first experiment is a change in the response to inflation in the policy rule, $\imath_\pi$. The experiment favors a significant increase in this response, consistent with the literature. As shown

[17]The procedure is similar to the one used to obtain the baseline calibration. However, the experiments do not include the restriction on a minimum level for the average bond spread and the equity premium.

[18]We considered additional experiments such as changing the parameters in the dividend growth process or, more interestingly, the volatility dynamics. None of these experiments provided insightful results.

in column (2) of the table, this change results, consistent with the data, in lower volatility of consumption growth and inflation, a lower autocorrelation of inflation, a less negative correlation of consumption growth and inflation, and lower R^2s of predictive regression of stock returns on macroeconomic volatility. However, the experiment also implies counterfactual changes such as reduced volatility and autocorrelation in the nominal interest rate, lower average bond spreads and equity premium, and increased predictability of bond returns on macroeconomic volatility. In addition, the model fails to capture the change from negative to positive of the correlation between consumption growth and the nominal interest rate. Column (3) in the table presents model moments implied by the experiment of changing the response to changes in the output gap in the policy rule, $\imath_z$. This experiment lowers this response, but has limited effect on both sets of macroeconomic and financial moments. Column (4) corresponds to the experiment of changing the parameter $\phi_{\pi z}$ in the equation linking inflation to the output gap. The experiment implies a slightly less negative parameter $\phi_{\pi z}$, and small changes in macroeconomic moments, a higher equity premium, and higher predictive power of macroeconomic volatility for asset returns. Finally, column (5) shows the moments related to the experiment of simultaneously changing $\imath_\pi$, $\imath_z$, and $\phi_{\pi z}$. The experiment favors significant increases in the responses to inflation and the change in the output gap in the policy rule, accompanied by a significantly positive coefficient $\phi_{\pi z}$. The results of the experiment are similar to those of only changing $\imath_\pi$ in column (2), with the advantage of capturing a positive correlation between consumption growth and the nominal interest rate, a sizable equity premium, and a reduction in the R^2s of predictive regressions for asset returns. However, the experiment fails to capture the increased volatility and autocorrelation of the nominal interest rate, a reduced correlation of this rate with consumption growth, and implies a counterfactually negative average bond spread. In summary, the first set of experiments tends to favor a stronger monetary policy response to inflation in the second subsample, possibly accompanied by a change in the structural link between the real economy and inflation which tends to reduce asset return predictability. However, changes in these coefficients do not seem sufficient to capture some important changes in macroeconomic dynamics during the period.

Table 9 reports model moments for the second set of experiments. Each experiment consists in changing the parameters describing individual shocks, while keeping all other parameters at baseline levels. The experiment on column (2) corresponds to changing the dynamics of the conditional mean of the natural rate of consumption growth, x_t. The experiment dramatically increases the autocorrelation coefficient of x_t and reduces its conditional volatility. This change reduces the volatilities of consumption growth and the nominal interest rate, with a noticeable increase in the autocorrelation of this rate, and no significant changes in targeted correlations of macroeconomic variables. In addition, R^2s of asset return predictive regressions on macroeconomic volatility tend to increase. The second experiment on column (3) consists of changing the parameters describing the dynamics of policy shocks u_t. This experiment implies a slightly higher autocorrelation for these shocks, with a lower average conditional volatility and a higher positive loading on the volatility process. These parameter changes have no noticeable effects on the volatility of consumption growth and inflation, tend to increase the volatility and autocorrelation of the nominal interest rate, considerably increase the average bond spread and equity premium, and increase the predictive power of macroeconomic volatility for stock returns without affecting the predictability for bond returns. The final experiment in this set changes the cost-push shock parameter. The experiment increases the autocorrelation of these shocks and reduces the negative loading of their conditional volatility on the volatility process. There are no significant effects on the targeted macroeconomic moments, a small reduction in the average bond spread and an increased equity premium. However, the change in the cost-push shock dynamics tends to reduce R^2s in asset return predictive regressions on macroeconomic volatility. In summary, the results of these experiments do not suggest that the observed changes in macroeconomic and financial variable dynamics are the result in the dynamics of the natural rate of consumption growth, favor a small change in the dynamics of policy and cost-push shocks to capture, respectively, a higher autocorrelation and volatility of the nominal interest rate, and lower R^2s in asset return predictive regressions. However, individual changes in shock dynamics have limited ability to explain all the changes observed in the second subsample.

Based on the results of the first set of experiments (changes in policy parameters), we conduct a third set of experiments similar to the second set but setting the response to inflation in the policy rule at the higher value, $\imath_\pi = 1.75$. Table 10 reports the experiment results. Qualitatively, most of the results are similar to those of the experiments in Table 9. As an advantage, increasing $\imath_\pi$ better captures changes in macroeconomic and financial moments, including the reduced asset return predictability. Notably, the only exception is the increase in the R^2s of the bond return predictive regressions resulting from changes in the cost-push shock dynamics. In summary, the experiments suggest that the observed changes in macroeconomic and financial variables documented for the period 1982-2008 are consistent with changes in both policy parameters and shock dynamics.

4.3 Cost-Push Shocks: Model Intuition and Empirical Evidence

The experiments above favor a reduction in asset return predictability resulting from more persistent cost-push shocks and reduced variation in the volatility of these shocks. To understand the economic intuition behind this result, consider the regression in equation

(1). The OLS slope coefficient and R^2 of this regression are

$$\beta_{p,j}^{k} = \frac{\text{cov}(r_{t\to t+p}^{k}, SV_t^j)}{\text{var}(SV_t^j)}, \quad \text{and} \quad R_{p,j}^{2,k} = \frac{\left(\beta_{p,j}^{k}\right)^2 \text{var}(SV_t^j)}{\text{var}(r_{t\to t+p}^{k})},$$

respectively. A reduced variation in the volatility of cost-push shocks translates into reduced responses of consumption growth, inflation, and their volatilities to volatility shocks. This, in combination with more persistent cost-push shocks, is reflected in a lower sensitivity of asset returns to volatility shocks, and a higher sensitivity to cost-push shocks. As a result, there is a significant reduction in the covariance of these returns with macroeconomic volatility relative to the reduction in the variance of macroeconomic volatility, which reduces $\beta_{p,j}^{k}$. In turn, the R^2 in the predictive regression declines.

Consistent with the model experiment, we find empirical support for both more persistent cost-push shocks and reduced variation in their volatility for the late subsample relative to the early one. Specifically, we rely on equation (8) to obtain estimates of cost-push shocks. This equation can be seen as a regression that links inflation to changes in the output gap and expected inflation, where the residuals capture cost-push shocks. Absolute or squared values of these residuals are measures of the volatility of these shocks. Table 11 reports first-order autocorrelations of cost-push shocks, ϵ_t, and their volatility calculated as the mean of the conditional volatility measures $abs(\epsilon_t)$ or ϵ_t^2, for our early and late samples. 1982QI is the cutoff point between the early and late subsamples, in line with the empirical analysis. Expected inflation in equation (8) is the one-period ahead fitted value of inflation from the benchmark 10-element VAR(4) employed in Section 2.2. The statistics show increased persistence and reduced conditional volatility in cost-push shocks from column (1) to column (2). This result provides empirical support to changes in the properties of cost-push shocks as an explanation of decreased asset return predictability in the late sample.

5 Conclusion

This paper documents and explores a significant predictive ability of the volatility of consumption growth, inflation, and a nominal short-term interest rate for U.S. stock and bond returns for the 1961-1977 period, followed by a decline in this ability after the Great Moderation. An equilibrium model with a monetary policy interest-rate rule and time-varying volatility in several economic shocks captures the documented asset return predictability. Experiments using the model suggest that both an increase in the response to inflation in the policy rule and changes in shock dynamics are required to explain the simultaneous reduction in macroeconomic volatility and return predictability. In particular, more persistent cost-push shocks with reduced variation in their volatility generate a decline in this predictability. The analysis can be useful to provide a better identification of the drivers of the Great Moderation by incorporating its implications on the relation between financial and macroeconomic variables. The model, however, relies on a reduced-form equation linking inflation and the real economy. Further work, where this link is obtained from first principles, is required to verify the validity of the theoretical results.

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Tables and Figures

Table 1: **Descriptive Statistics of U.S. Macroeconomic and Financial Data in the Post-war Sample for Quarterly Observations**

The macro variables are log consumption growth (Δc), inflation (π), log output gap (z), and the nominal short-term interest rate (i). The financial variables are log dividend yield ($d-p$), log dividend growth (Δd), log equity return (Stock), and log return of the 5-year to maturity nominal bond (Bond). Mean, standard deviation, first-order autocorrelations and correlations are reported. Panel A covers the full sample from 1961QIII to 2008QIII, panel B covers the early subsample from 1961QIII to 1976QIV, and panel C covers the late subsample from 1982QI to 2008QIII. Sources: FRED database, CRSP, and Board of Governors of the Federal Reserve System.

	Mean	Volatility	AR(1)	Correlations							
				Δc	π	z	i	$d-p$	Δd	Stock	Bond
Panel A: Full Sample 1961QIII to 2008QIII											
Δc	0.507	0.456	0.425	1.000							
π	0.931	0.590	0.877	-0.228	1.000						
z	0.065	1.498	0.863	0.010	0.048	1.000					
i	5.623	2.809	0.926	-0.073	0.610	0.158	1.000				
dp	-4.867	0.358	0.949	-0.065	0.628	-0.084	0.659	1.000			
Δd	1.515	8.637	-0.716	0.075	0.031	0.005	0.018	0.135	1.000		
Stock	2.382	7.930	0.033	0.167	-0.084	-0.204	-0.005	-0.050	0.058	1.000	
Bond	1.789	3.457	-0.061	-0.150	-0.066	-0.204	-0.056	0.080	-0.022	0.162	1.000
Panel B: Early Sample 1961QIII to 1976QIV											
Δc	0.651	0.517	0.364	1.000							
π	1.064	0.648	0.860	-0.412	1.000						
z	-0.109	1.622	0.849	0.039	-0.113	1.000					
i	4.969	1.495	0.886	-0.342	0.765	0.235	1.000				
dp	-4.799	0.171	0.686	-0.385	0.629	-0.366	0.398	1.000			
Δd	1.440	10.251	-0.684	0.045	0.069	-0.061	0.008	0.327	1.000		
Stock	1.644	8.996	0.106	0.262	-0.188	-0.315	-0.279	-0.222	0.040	1.000	
Bond	1.270	2.423	-0.045	0.003	0.139	-0.260	-0.096	0.217	0.021	0.293	1.000
Panel C: Late Sample 1982QI to 2008QIII											
Δc	0.461	0.376	0.424	1.000							
π	0.663	0.262	0.614	-0.084	1.000						
z	-0.021	1.340	0.916	0.026	-0.176	1.000					
i	5.198	2.575	0.952	0.276	0.515	-0.039	1.000				
dp	-4.999	0.376	0.961	0.064	0.581	-0.249	0.685	1.000			
Δd	1.416	8.057	-0.740	0.110	-0.140	0.029	-0.007	0.096	1.000		
Stock	2.826	7.424	-0.020	0.186	-0.012	-0.153	0.122	0.025	0.076	1.000	
Bond	2.305	3.384	0.103	-0.136	0.052	-0.168	0.145	0.251	-0.058	0.008	1.000

Table 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 1961QIII to 2008QIII. Sources: FRED database and Board of Governors of the Federal Reserve System.

	(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 3: **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: ouput 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 rate (i). Four lags are included in the VAR, but only the loadings on the first lag are shown. For brevity, only four equations pertinent to the predictive regressions are displayed: consumption growth, inflation, output gap, and the nominal short rate. Panel A covers the full sample from 1961QIII to 2008QIII, panel B covers the early subsample from 1961QIII to 1976QIV, and panel C covers the late subsample from 1982QI to 2008QIII. Source: FRED database.

	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}	z_{t-1}	i_{t-1}
Panel A: Full Sample 1961QIII to 2008QIII											
Δc_t	0.010	-0.090	-0.132	0.053	-0.054	0.005	0.126	0.021	-0.004	1.155	0.031
π_t	0.148	-0.020	0.027	0.037	0.029	0.005	0.109	-0.030	0.199	-0.263	-0.023
z_t	0.041	0.061	0.143	0.306	0.012	-0.043	-0.289	0.033	-0.293	0.834	0.025
i_t	-0.374	-0.126	-0.133	0.043	-0.095	0.015	-0.184	-0.005	-0.572	2.668	-0.047
Panel B: Early Sample 1961QIII to 1976QIV											
Δc_t	0.632	-0.219	-0.161	0.277	0.399	0.009	0.455	0.004	0.398	1.770	0.040
π_t	0.160	0.320	-0.242	-0.066	-0.225	-0.061	0.003	-0.063	0.132	-0.558	0.092
z_t	1.654	-0.078	0.513	0.363	0.362	0.007	-0.387	0.068	0.411	5.675	0.047
i_t	2.200	-0.403	0.123	-0.211	-0.544	0.163	-0.926	0.146	0.653	3.154	0.068
Panel C: Late Sample 1982QI to 2008QIII											
Δc_t	-0.150	-0.030	-0.159	-0.008	-0.039	0.018	0.122	-0.018	0.188	0.101	0.078
π_t	0.000	0.133	-0.105	-0.114	0.018	-0.006	0.041	-0.009	0.329	0.502	-0.082
z_t	0.363	0.143	-0.132	0.278	-0.015	-0.083	-0.037	-0.023	-0.044	-0.947	0.069
i_t	-0.376	0.266	-0.315	-0.177	-0.219	-0.051	-0.020	0.004	-0.120	2.944	0.065

Table 4: **Conditional Mean and Conditional Variance Break Points of Macroeconomic Volatility Series Estimated by QLR Statistics**

This table reports the estimated break points in the conditional mean and the conditional variance of th volatilities of 10 macroeconomic variables: Δy is log output growth, Δc is log consumption growth, Δh is log hours growth, Δw is log wage growth, Δinv is log investment growth, Δg is log government spending growth, $\Delta \tau$ is log government revenue growth, π is log inflation, x is log output gap, i is the nominal short rate. The analysis assumes AR(1) models for volatility. $*$ denotes statistical significance at the 10% level. $**$ denotes statistical significance at the 5% level. $***$ denotes statistical significance at the 1% level. Source: FRED database.

	ABS		SQR		GARCH-ABS		GARCH-SQR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	mean	variance	mean	variance	mean	variance	mean	variance
Δy	1983QIII	1983QIV**	1983QIII	1982QI ***	1981QI	1981QI ***	1981QI	1980QIV**
Δc	1992QIV**	1969QIV***	1981QIV**	1969QIV**	1979QIV	1969QIII**	1979QIV	1983QI **
Δh	1976QI	1981QIV***	1975QIII **	1981QII **	1974QII	1980QIV*	1974QII	1979QII
Δw	1989QI	1991QII	1997QIV	1991QII*	1987QIV	1986QII	1987QIV	1987QIV
Δinv	1974QIII ***	1983QII***	1971QII***	1984QII***	1973QII*	1982QIII**	1973QII	1981QIV ***
Δg	2001QIV	1970QI	1969QIV	1970QI ***	2000QIII	2000QIV	2000QIII	1969QIII
$\Delta \tau$	1975QIII	2001QIV	1975QIII**	1975QIV	1984QI	1998QIII	1974QI	1974QI
π	1986QII	1978QIII ***	1978QII **	1978QIII ***	1990QI	1977QI **	1977QI	1977QI **
z	1983QIII	1984QII*	1983QIII	1982QI **	1981QI	1980QIII**	1981QI	1980QIII**
i	1985QIII***	1985QIV**	1980QIII ***	1985QIV **	1984QII	1982QII	1979QI ***	1984QIII

Table 5: **Out of Sample Forecast Root Mean Square Error (RMSE)**

Out of sample return forecast performed with an expanding estimation window within the full, early, and late samples. In each case, macroeconomic conditional volatilities are constructed from the benchmark 10-vector VAR using only the first half of observations in the given sample as the initial estimation window. Residuals of the consumption growth, the inflation, the output gap, and the nominal short rate equations are then transformed by GARCH-ABS to obtain conditional volatilities. 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 RMSE is calculated from the difference between forecasted and realized returns. Sources: FRED database, CRSP, and Board of Governors of the Federal Reserve System.

	Conditional Volatility	(1) Stock Forecast Error	(2) Bond Forecast Error
12 Quarter Ahead Cumulative Return			
Full Sample	Δc	0.2439	0.0965
	π	0.2412	0.0986
	z	0.2365	0.1084
	i	0.2476	0.1026
Early Sample	Δc	0.2735	0.1042
	π	0.2492	0.1063
	z	0.2398	0.1049
	i	0.242	0.1092
Late Sample	Δc	0.3232	0.1426
	π	0.3426	0.1367
	z	0.3306	0.1145
	i	0.3306	0.1203
16 Quarter Ahead Cumulative Return			
Full Sample	Δc	0.2871	0.1066
	π	0.2867	0.1118
	z	0.2853	0.1309
	i	0.2955	0.1265
Early Sample	Δc	0.2855	0.1269
	π	0.2209	0.1281
	z	0.2232	0.1251
	i	0.2039	0.1335
Late Sample	Δc	0.3871	0.1711
	π	0.4068	0.166
	z	0.3873	0.1278
	i	0.3929	0.1437
20 Quarter Ahead Cumulative Return			
Full Sample	Δc	0.3156	0.1173
	π	0.3164	0.1233
	z	0.3173	0.1481
	i	0.3311	0.1484
Early Sample	Δc	0.3798	0.1689
	π	0.3574	0.1806
	z	0.2909	0.1721
	i	0.1853	0.1951
Late Sample	Δc	0.4423	0.184
	π	0.4507	0.1801
	z	0.4306	0.1295
	i	0.4397	0.1581

Table 6: **Baseline Calibration**

Parameter values implied by the baseline calibration. The values are chosen to minimize deviations of a set of macroeconomic and financial moments implied by the model relative to their data counterparts for the 1961:Q1-1977:Q4 period.

Variable (calibrated)	Variable Description	Value
β	Subjective discount factor	0.9969
γ	Risk aversion	30.0000
ψ	Elasticity of intertemporal substitution	1.4386
$\bar{\sigma}_c$	Constant term of consumption growth volatility	0.0000
ϕ_x	Autoregressive coefficient of the conditional mean of consumption growth	0.0000
$\bar{\sigma}_x \times 10^3$	Constant term of the volatility of the conditional mean of consumption growth	0.3508
σ_{xv}	Loading on v_t of the volatility of the conditional mean of consumption growth	-4.1536
$\phi_{\pi z}$	Sensitivity of inflation to the output gap	-0.5415
β_π	Sensitivity of inflation to expected inflation	0.9909
i_π	Interest-rate rule coefficient on inflation	1.4594
i_z	Interest-rate rule coefficient on output gap	-0.3546
ϕ_u	Autoregressive coefficient of the monetary policy shock	0.6325
$\bar{\sigma}_u \times 10^3$	Constant term of the monetary policy shock volatility	4.5865
σ_{uv}	Loading on v_t of the volatility of the monetary policy shock	4.2775
ϕ_ϵ	Autoregressive coefficient of the cost-push shock	0.0000
$\bar{\sigma}_\epsilon \times 10^3$	Constant term of the cost-push shock volatility	3.4841
$\sigma_{\epsilon v}$	Loading on v_t of the volatility of the cost-push shock	-1.2848
ϕ_{dc}	Autoregressive coefficient of dividend growth	4.7385
$\bar{\sigma}_d \times 10^3$	Constant term of dividend growth volatility	19.6835
σ_{dc}	Loading of dividend growth on consumption growth shocks	-29.8890
σ_{dv}	Loading on v_t of the volatility of dividend growth	-2.5531
ϕ_v	Autoregressive coefficient of volatility	0.9852
$\sigma_v \times 10^6$	Volatility of the volatility process	1.6575
Variable (fixed)		
μ_c	Unconditional mean of consumption growth	0.0064
$\bar{\imath}$	Constant in the interest-rate policy rule	0.0125

Table 7: **Model and Data Moments**

Data statistics are for the subsamples 1961:Q3-1977:Q4 and 1982:Q1-2008:Q3. Model moments are computed based on 1,000 simulations of 1,000 periods each, using the parameters in Table 6. "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.

	Basic Moments					**Correlations**			**Predictability R^2's (%)**			
Variable	Mean (%)*	SD (%)	AC	Mean CVol (%)	SD CVol (%)	π	i	Δd	$r_d(0,20)$ on Level	$r^{(20)}(0,20)$ on Level	$r_d(0,20)$ on Vol	$r^{(20)}(0,20)$ on Vol
Model Baseline Calibration												
Δc	0.64	0.73	-0.02	0.0040	0.0069	-0.38	-0.42	0.44	0.46	0.31	1.80	5.71
π	0.56	0.55	0.60	0.0019	0.0034		0.72	-0.21	2.24	11.51	1.93	6.97
i	1.25	0.40	0.48	0.0012	0.0026			-0.10	8.38	36.40	2.42	9.01
Δd	0.64	2.87	0.08	0.0516	0.0757				0.09	0.11	0.37	1.25
r	0.63	0.31	0.19									
p_d	4.74	14.63	0.95									
r_d	2.08	4.42	-0.07									
$r^{(20)}$	1.57	1.28	-0.02									
$y^{(20)} - i$	0.18											
$r_d - i$	0.83											
Data 1961:Q3 - 1977:Q4												
Δc	0.64	0.51	0.35	0.0020	0.0029	-0.38	-0.32	0.08	4.07	0.55	0.21	0.02
π	1.10	0.65	0.85	0.0009	0.0014		0.76	0.02	41.85	63.65	3.64	7.75
i	1.25	0.37	0.88	0.0003	0.0004			-0.03	47.75	52.59	14.92	16.56
Δd	0.44	10.14	-0.68	0.5299	0.8925				0.14	1.14	14.12	19.13
r	0.15	0.44	0.61									
p_d	4.78	18.87	0.74									
r_d	1.47	8.87	0.09									
$r^{(20)}$	1.21	2.41	-0.09									
$y^{(20)} - i$	0.19											
$r_d - i$	0.96											
Data 1982:Q1 - 2008:Q3												
Δc	0.46	0.38	0.43	0.0011	0.0022	-0.13	0.24	0.11	5.96	6.85	0.34	1.31
π	0.67	0.28	0.65	0.0004	0.0005		0.55	-0.15	19.53	45.42	0.93	3.82
i	1.31	0.66	0.95	0.0003	0.0013			-0.02	4.99	82.07	8.74	8.51
Δd	0.77	8.10	-0.74	0.2798	0.6005				0.01	0.00	1.30	0.21
r	0.64	0.56	0.85									
p_d	4.99	38.23	0.96									
r_d	2.87	7.44	-0.03									
$r^{(20)}$	2.39	3.51	-0.10									
$y^{(20)} - i$	0.35											
$r_d - i$	0.96											

* Except for p_d (level).

Table 8: **Model Experiments - Changing Policy Parameters**

Model moments are computed using the parameters in Table 6, 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)
	Baseline Calibration	Experiments			
Moments	$i_\pi = 1.46$, $i_z = -0.35$, $\phi_{\pi z} = -0.54$	$i_\pi = 2.13$	$i_z = -0.5$	$\phi_{\pi z} = -0.44$	$i_\pi = 2.95$, $i_z = 1$, $\phi_{\pi z} = 0.66$
$SD(\Delta c)$	0.73	0.70	0.68	0.81	0.55
$SD(\pi)$	0.55	0.36	0.52	0.51	0.29
$SD(i)$	0.40	0.32	0.37	0.37	0.36
$SD(\Delta d)$	2.87	2.77	2.85	2.93	2.72
$SD(r)$	0.31	0.29	0.31	0.32	0.28
$SD(p_d)$	14.63	3.84	12.01	18.27	15.96
$SD(r_d)$	4.42	3.09	4.06	5.04	4.16
$SD(y^{(20)})$	0.30	0.19	0.27	0.27	0.09
$SD(r^{(20)})$	1.28	0.87	1.16	1.15	0.74
$AC(\pi)$	0.60	0.56	0.58	0.59	0.50
$AC(i)$	0.48	0.28	0.42	0.44	0.30
$corr(\Delta c, \pi)$	-0.38	-0.20	-0.33	-0.35	0.00
$corr(\Delta c, i)$	-0.42	-0.33	-0.43	-0.41	0.30
$corr(\pi, i)$	0.72	0.63	0.68	0.65	0.73
$E[y^{(20)}) - i]$	0.18	0.02	0.15	0.19	-0.08
$E[r_d - i]$	0.83	0.09	0.67	1.24	0.87
R^2 of $r_d(0,20)$ on Δc $CVol$	1.80	0.41	1.19	2.36	1.10
R^2 of $r_d(0,20)$ on π $CVol$	1.93	0.19	1.22	2.13	0.44
R^2 of $r_d(0,20)$ on i $CVol$	2.42	0.53	1.81	3.82	0.74
R^2 of $r_d(0,20)$ on Δd $CVol$	0.37	0.08	0.22	0.43	0.06
R^2 of $r^{(20)}(0,20)$ on Δc $CVol$	5.71	8.25	5.10	5.94	6.85
R^2 of $r^{(20)}(0,20)$ on π $CVol$	6.97	6.37	6.16	5.89	2.94
R^2 of $r^{(20)}(0,20)$ on i $CVol$	9.01	11.65	9.53	11.00	4.84
R^2 of $r^{(20)}(0,20)$ on Δd $CVol$	1.25	0.40	0.92	1.14	0.16

Table 9: **Model Experiments - Changing Shock Parameters**

Model moments are computed using the parameters in Table 6, 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)
		Experiments		
Moments	Baseline Calibration	$\phi_x = 0.99$, $\bar{\sigma}_x = 2.25 \times 10^{-5}$, $\sigma_{xv} = 0$	$\phi_u = 0.66$, $\bar{\sigma}_u = 0.0029$, $\sigma_{uv} = 5$	$\phi_\epsilon = 0.25$, $\bar{\sigma}_\epsilon = 0.0034$, $\sigma_{\epsilon v} = -0.71$
$SD(\Delta c)$	0.73	0.58	0.71	0.70
$SD(\pi)$	0.55	0.54	0.53	0.56
$SD(i)$	0.40	0.28	0.42	0.39
$SD(\Delta d)$	2.87	2.22	2.85	2.91
$SD(r)$	0.31	0.16	0.31	0.32
$SD(p_d)$	14.63	19.15	17.99	12.30
$SD(r_d)$	4.42	4.56	4.89	4.00
$SD(y^{(20)})$	0.30	0.26	0.36	0.27
$SD(r^{(20)})$	1.28	1.06	1.50	1.20
$AC(\pi)$	0.60	0.63	0.62	0.58
$AC(i)$	0.48	0.86	0.52	0.39
$corr(\Delta c, \pi)$	-0.38	-0.40	-0.33	-0.34
$corr(\Delta c, i)$	-0.42	-0.36	-0.40	-0.28
$corr(\pi, i)$	0.72	0.79	0.75	0.76
$E[y^{(20)}) - i]$	0.18	0.19	0.23	0.16
$E[r_d - i]$	0.83	1.33	1.12	0.88
R^2 of $r_d(0,20)$ on Δc $CVol$	1.80	1.42	2.69	0.56
R^2 of $r_d(0,20)$ on π $CVol$	1.93	5.64	2.80	1.28
R^2 of $r_d(0,20)$ on i $CVol$	2.42	6.11	2.97	1.69
R^2 of $r_d(0,20)$ on Δd $CVol$	0.37	0.09	0.60	0.17
R^2 of $r^{(20)}(0,20)$ on Δc $CVol$	5.71	2.91	6.55	2.40
R^2 of $r^{(20)}(0,20)$ on π $CVol$	6.97	11.38	7.44	6.34
R^2 of $r^{(20)}(0,20)$ on i $CVol$	9.01	12.30	8.46	8.83
R^2 of $r^{(20)}(0,20)$ on Δd $CVol$	1.25	0.13	1.59	0.54

Table 10: **Model Experiments - Changing Shock Parameters and $\imath_\pi$**

Model moments are computed using the parameters in Table 6, 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)
		Experiments		
Moments	Baseline Calibration	$\phi_x = 0.92$, $\bar{\sigma}_x = 0.0007$, $\sigma_{xv} = 0.01$	$\phi_u = 0.77$, $\bar{\sigma}_u = 0.0029$, $\sigma_{uv} = 5$	$\phi_\epsilon = 0.28$, $\bar{\sigma}_\epsilon = 0.003$, $\sigma_{\epsilon v} = -0.93$
$SD(\Delta c)$	0.73	0.58	0.69	0.65
$SD(\pi)$	0.55	0.45	0.58	0.46
$SD(i)$	0.40	0.30	0.47	0.37
$SD(\Delta d)$	2.87	2.26	2.82	2.86
$SD(r)$	0.31	0.16	0.30	0.31
$SD(p_d)$	14.63	16.98	20.27	5.87
$SD(r_d)$	4.42	4.86	5.36	3.20
$SD(y^{(20)})$	0.30	0.21	0.45	0.25
$SD(r^{(20)})$	1.28	1.16	1.98	1.11
$AC(\pi)$	0.60	0.64	0.73	0.57
$AC(i)$	0.48	0.88	0.59	0.36
$corr(\Delta c, \pi)$	-0.38	-0.21	-0.27	-0.27
$corr(\Delta c, i)$	-0.42	-0.06	-0.39	-0.20
$corr(\pi, i)$	0.72	0.72	0.83	0.73
$E[y^{(20)}) - i]$	0.18	-0.02	0.27	0.06
$E[r_d - i]$	0.83	1.15	1.11	0.33
R^2 of $r_d(0,20)$ on Δc $CVol$	1.80	1.23	3.81	0.43
R^2 of $r_d(0,20)$ on π $CVol$	1.93	2.49	3.35	0.33
R^2 of $r_d(0,20)$ on i $CVol$	2.42	1.87	1.39	0.70
R^2 of $r_d(0,20)$ on Δd $CVol$	0.37	0.07	0.55	0.10
R^2 of $r^{(20)}(0,20)$ on Δc $CVol$	5.71	3.37	9.05	5.04
R^2 of $r^{(20)}(0,20)$ on π $CVol$	6.97	7.51	8.95	5.37
R^2 of $r^{(20)}(0,20)$ on i $CVol$	9.01	5.74	4.25	10.48
R^2 of $r^{(20)}(0,20)$ on Δd $CVol$	1.25	0.10	1.46	0.49

Table 11: **Cost-Push Shocks in the Data**

First-order autoregressive coefficients and mean conditional volatilities of cost-push shocks estimated in the data. The estimation equation is taken from the theoretical model such that:

$$\pi_t = a_\pi + \phi_{\pi z}\Delta z_t + \beta_\pi \mathbb{E}_t[\pi_{t+1}] + \epsilon_t,$$

where π is inflation, Δz_t is the growth rate of the output gap, $\mathbb{E}_t[\pi_{t+1}]$ is the inflation expectation at time t, and ϵ_t is the cost push shock. Inflation expectations are the one-period ahead fitted values of inflation from the benchmark 10-element VAR(4) used in the empirical analysis. Conditional volatilities of the cost-push shocks are calculated as absolute or squared values of ϵ_t. 1982QI is the cutoff point for the two subsamples, consistent with the empirical analysis. The first five observations of the sample are not used due to the 4 lags in the VAR and the one period forecast for inflation expectation. Source: FRED database.

	(1) Early Sample 1965QIV to 1981QIV	(2) Late Sample 1982QI to 2008QIII
AR(1) Coefficient of ϵ_t	0.0313	0.1295
Mean Conditional Volatility $abs(\epsilon_t)$	0.1737	0.1142
Mean Conditional Volatility ϵ_t^2	0.0537	0.0227

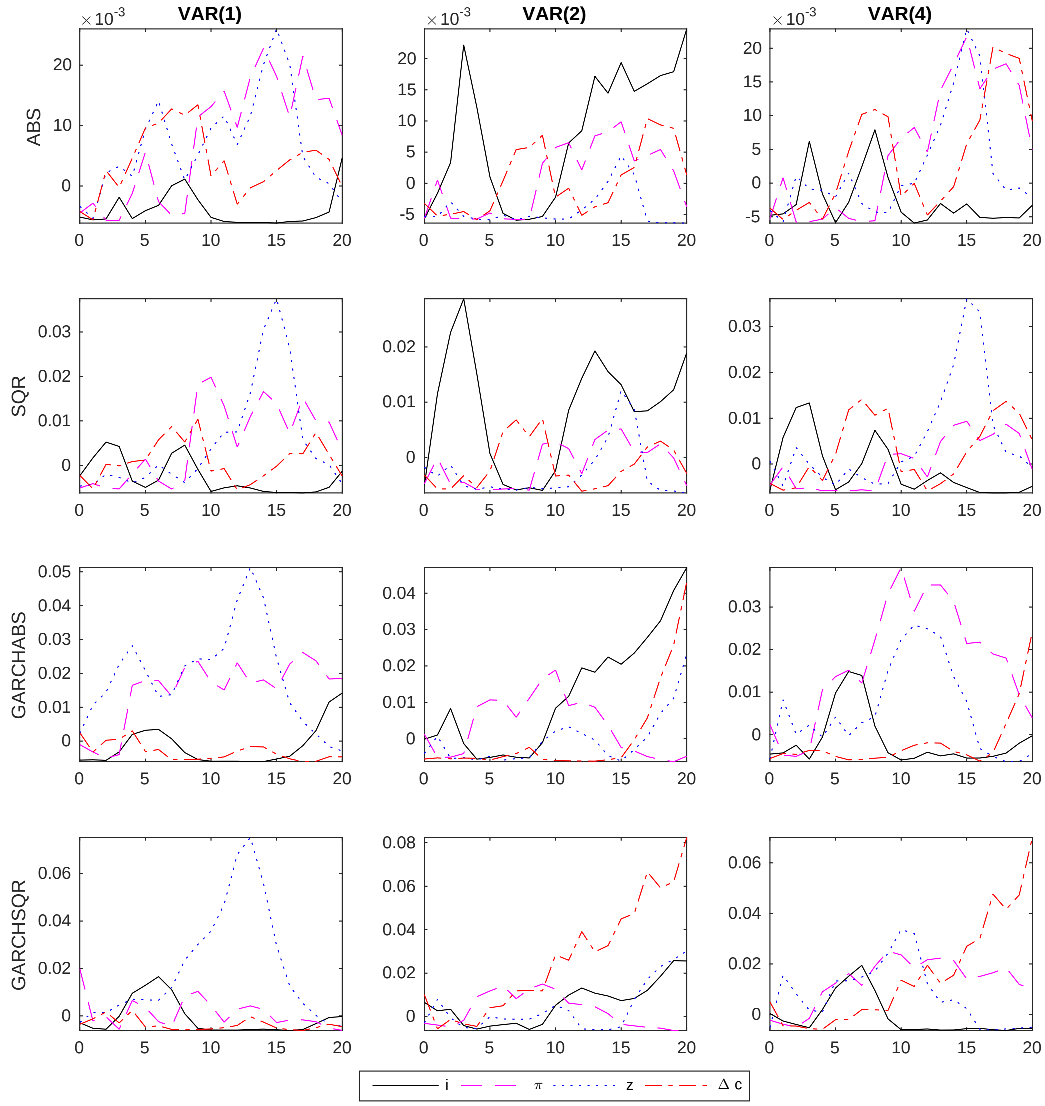


Figure 1: Adjusted R^2 of univariate predictive regressions for the full sample from 1961QIII to 2008QIII. The dependent variables are cumulative log equity returns from time t up to $t + 20$, or up to 5 years. The regressors are conditional volatilities of the nominal short rate (i), inflation (π), the output gap (z), and consumption growth (Δc). Each subplot represents a different construction of conditional volatilities: VAR lags in columns and residuals transformations in rows. Sources: FRED database and CRSP.

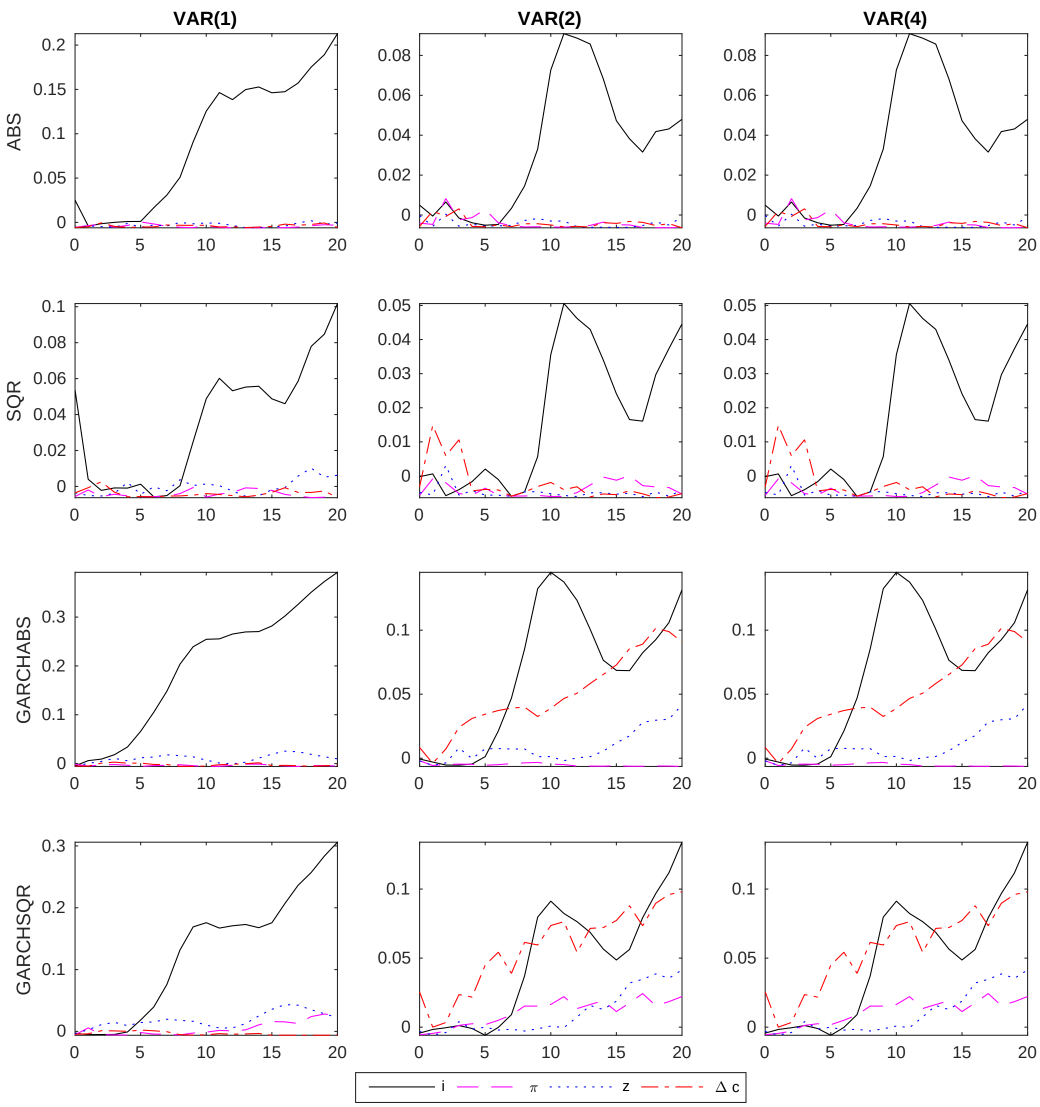


Figure 2: Adjusted R^2 of univariate predictive regressions for the full sample from 1961QIII to 2008QIII. The dependent variables are cumulative log 5-YTM bond returns from time t up to $t+20$, or up to 5 years. The regressors are conditional volatilities of the nominal short rate (i), inflation (π), the output gap (z), and consumption growth (Δc). Each subplot represents a different construction of conditional volatilities: VAR lags in columns and residuals transformations in rows. Sources: FRED database and Board of Governors of the Federal Reserve System.

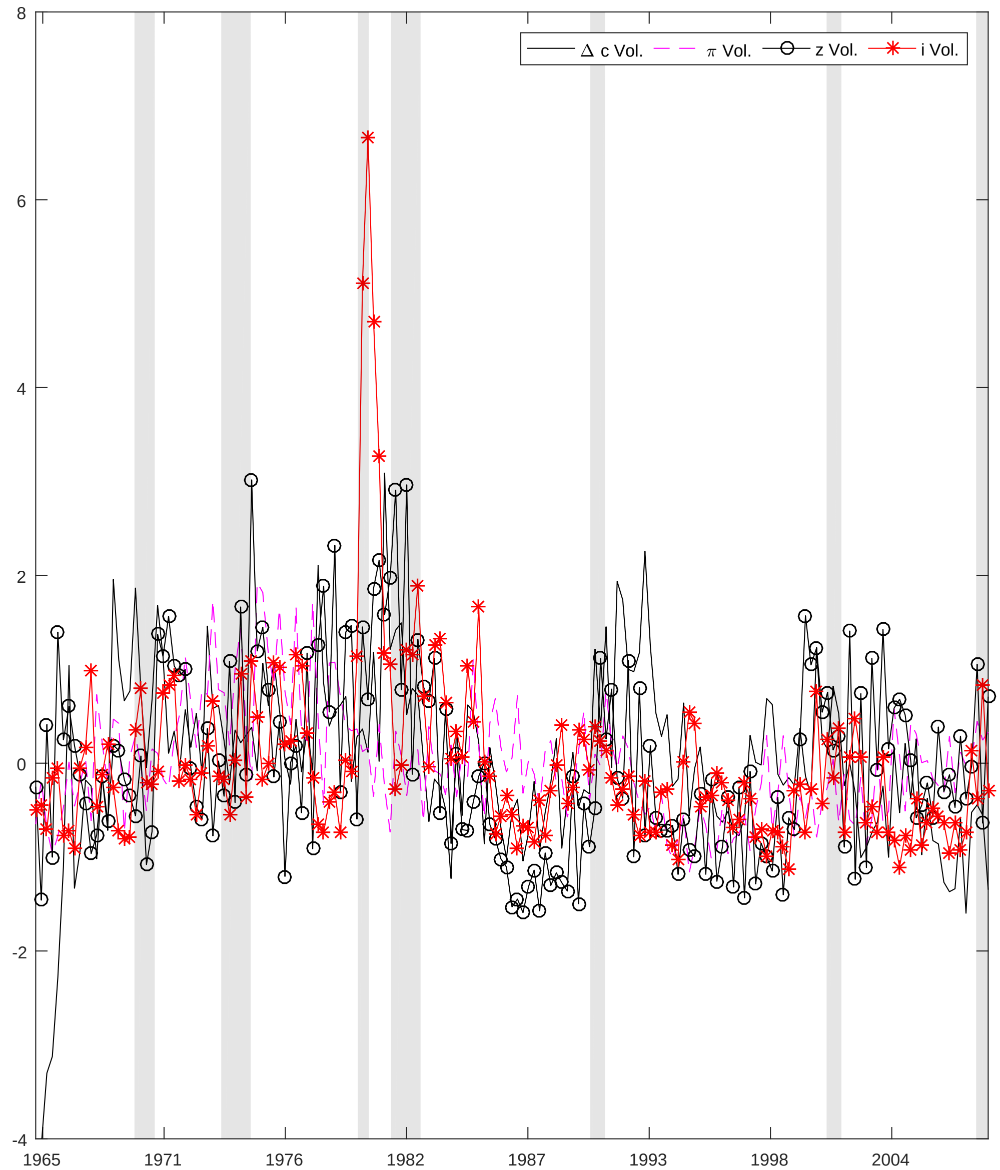
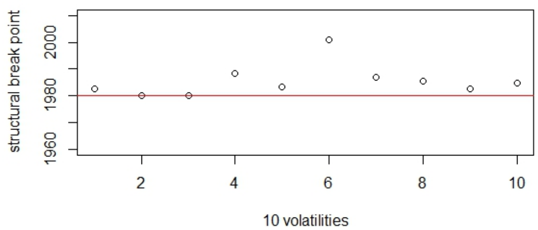
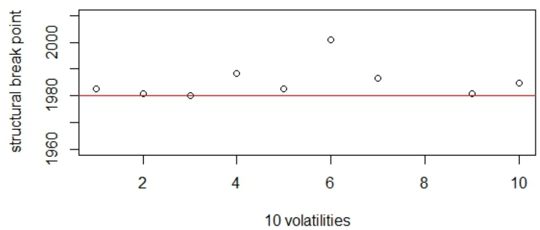


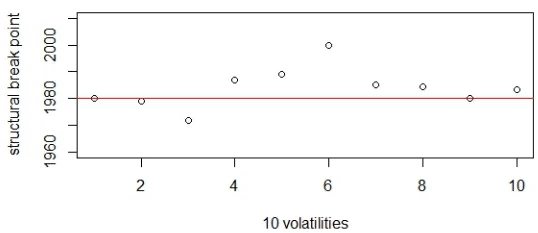
Figure 3: Time series plot of the four volatility series estimated by the benchmark 10-element 4-lag VAR, and the residuals are transformed by the GARCH absolute value model. The conditional volatilities are: consumption growth (Δc), inflation (π), the output gap (z), and the nominal short rate (i). NBER recession bars are shaded in gray. Source: FRED database.



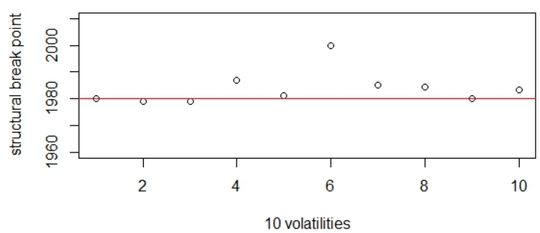
(a) absolute errors



(b) squared errors

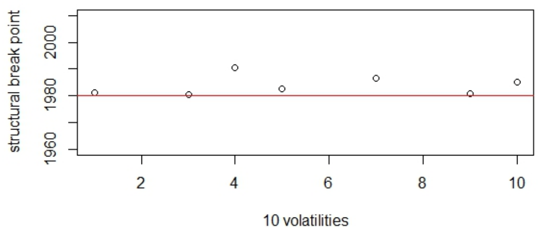


(c) GARCH absolute errors

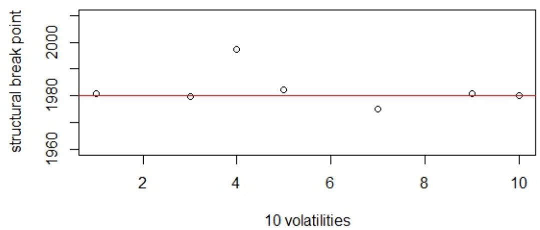


(d) GARCH squared errors

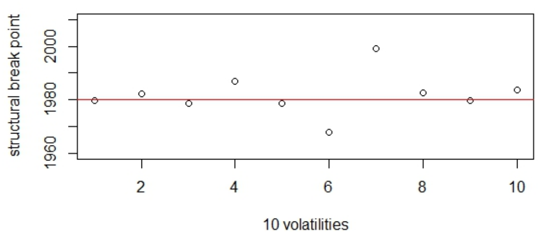
Figure 4: CUSUM test of volatility series in the full sample from 1961QIII to 2008QIII. Each subplot from (a) to (d) corresponds to a different measure of volatility by transforming the residuals from the VAR. The y-axis is labeled from 1961 to 2008, with the red line denoting 1980. The x-axis represents the ordering of the variables from the VAR. They are, in order from 1 to 10, log output growth, log consumption growth, log hours growth, log wage growth, log investment growth, log government spending growth, log government revenue growth, log inflation, log output gap, and the nominal short rate. Source: FRED database.



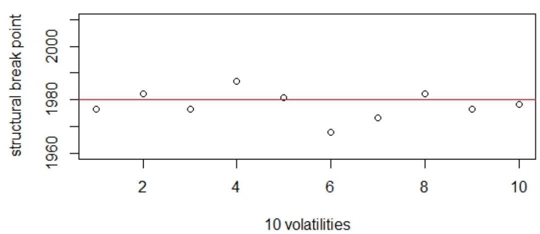
(a) absolute errors



(b) squared errors



(c) GARCH absolute errors



(d) GARCH squared errors

Figure 5: CUSUM test of the absolute value of volatility series in the full sample from 1961QIII to 2008QIII. Each subplot from (a) to (d) corresponds to a different measure of volatility by transforming the residuals from the VAR. The y-axis is labeled from 1961 to 2008, with the red line denoting 1980. The x-axis represents the ordering of the variables from the VAR. They are, in order from 1 to 10, log output growth, log consumption growth, log hours growth, log wage growth, log investment growth, log government spending growth, log government revenue growth, log inflation, log output gap, and the nominal short rate. Source: FRED database.

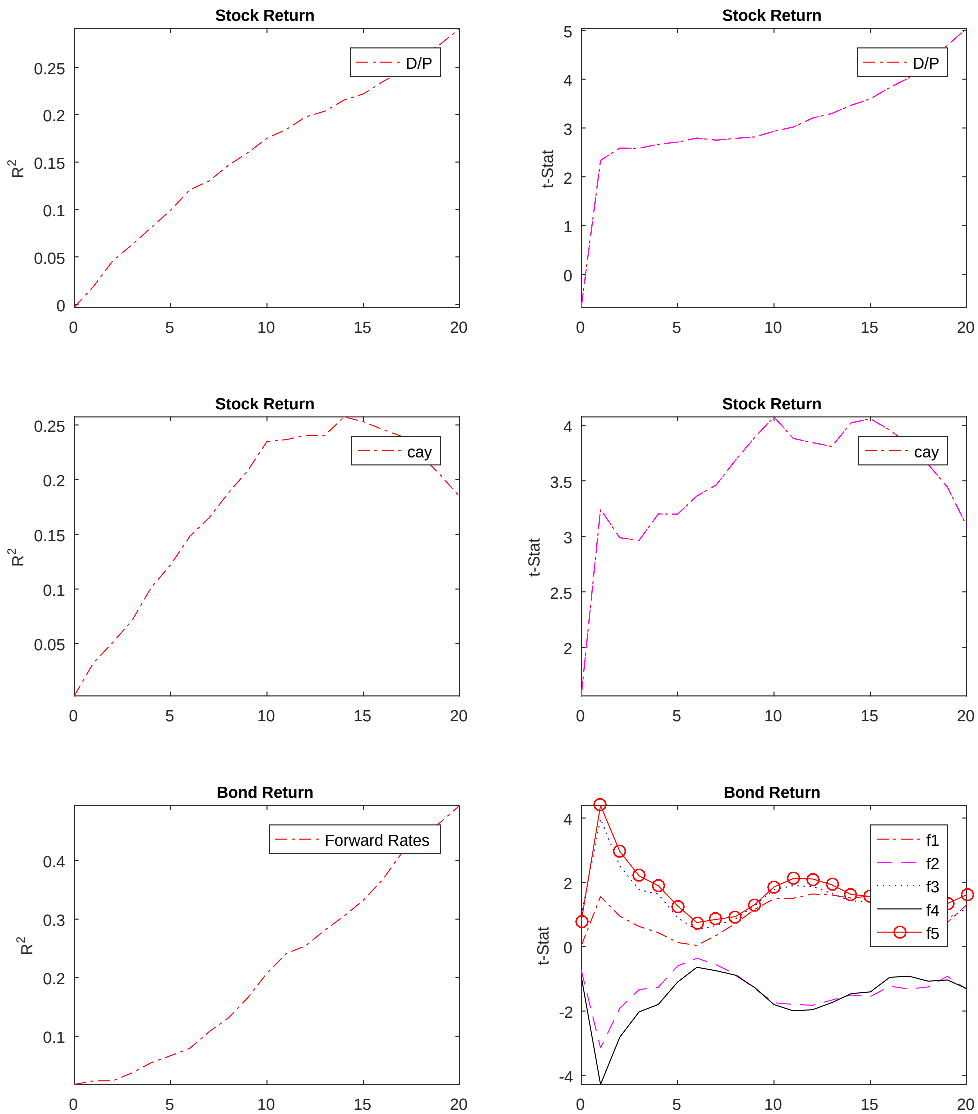


Figure 6: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961QIII to 2008QIII. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first and second rows) and nominal bonds (the third rows). The regressors for equity returns are dividend yield and *cay*, respectively. The regressors for bond returns are Cochrane and Piazzesi (2005) forward rates. Macroeconomic volatilities are not included in the predictive regressions. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Sources: CRSP and Board of Governors of the Federal Reserve System.

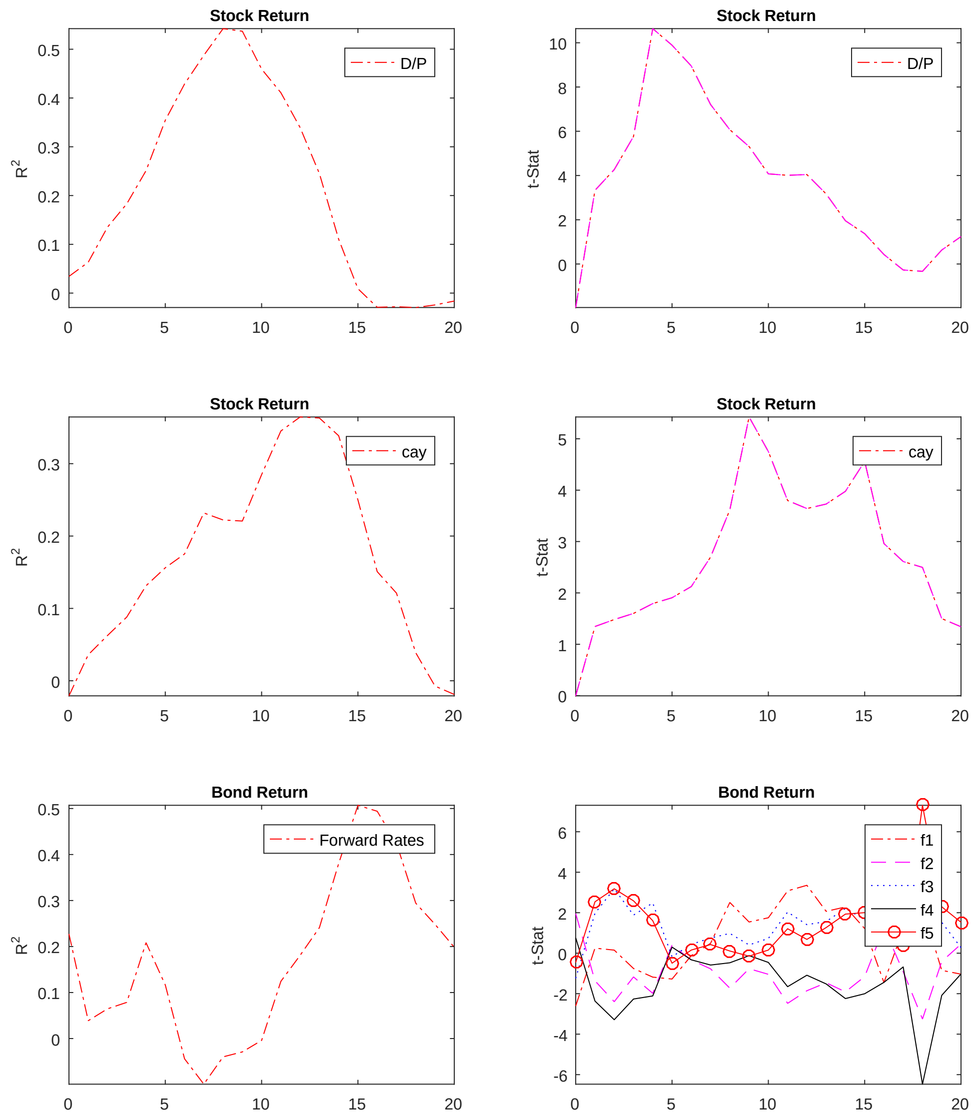


Figure 7: Adjusted R^2 and t-statistics of predictive regressions for the early sample from 1961QIII to 1976QIV. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first and second rows) and nominal bonds (the third rows). The regressors for equity returns are dividend yield and *cay*, respectively. The regressors for bond returns are Cochrane and Piazzesi (2005) forward rates. Macroeconomic volatilities are not included in the predictive regressions. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Sources: CRSP and Board of Governors of the Federal Reserve System.

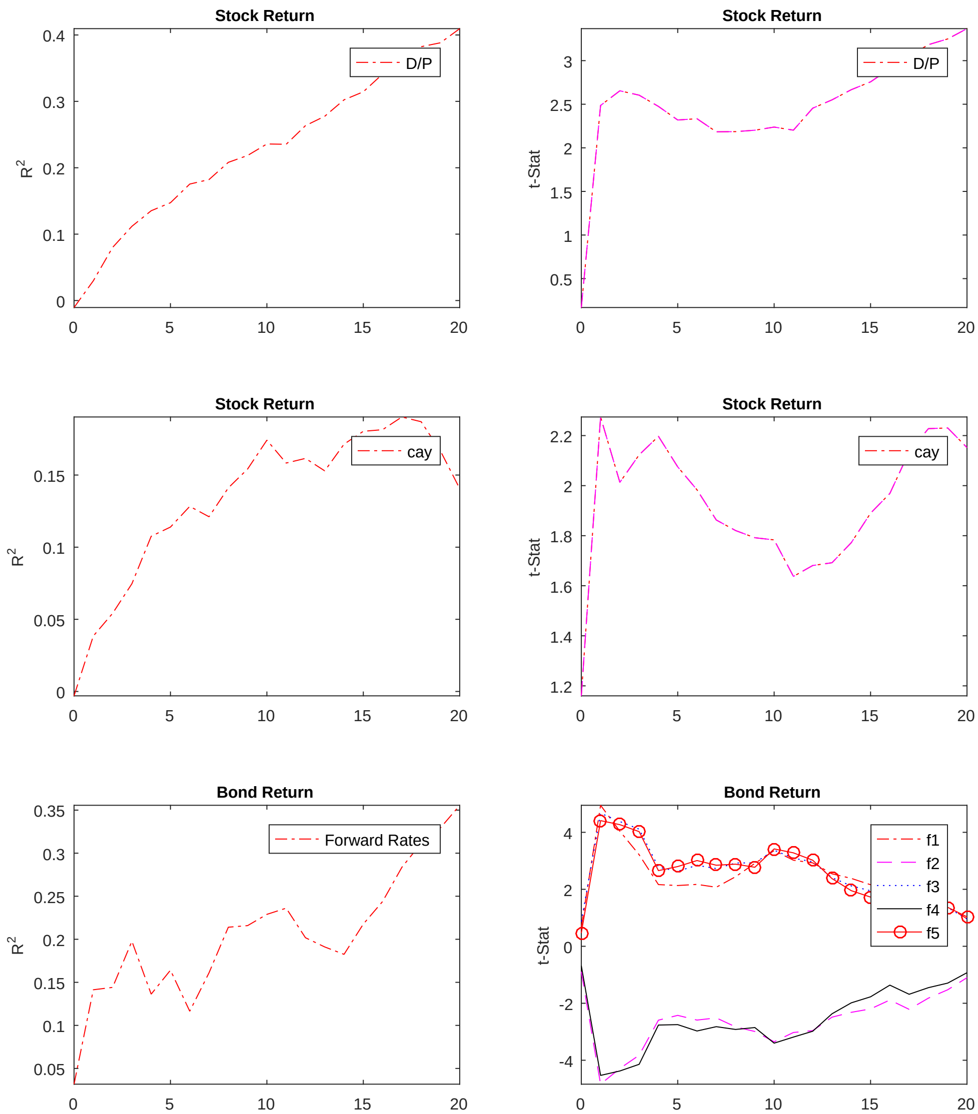


Figure 8: Adjusted R^2 and t-statistics of predictive regressions for the late sample from 1982QI to 2008QIII. The dependent variables are cumulative log returns from time t up to $t + 20$, or up to 5 years, for equity (the first and second rows) and nominal bonds (the third rows). The regressors for equity returns are dividend yield and *cay*, respectively. The regressors for bond returns are Cochrane and Piazzesi (2005) forward rates. Macroeconomic volatilities are not included in the predictive regressions. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Sources: CRSP and Board of Governors of the Federal Reserve System.

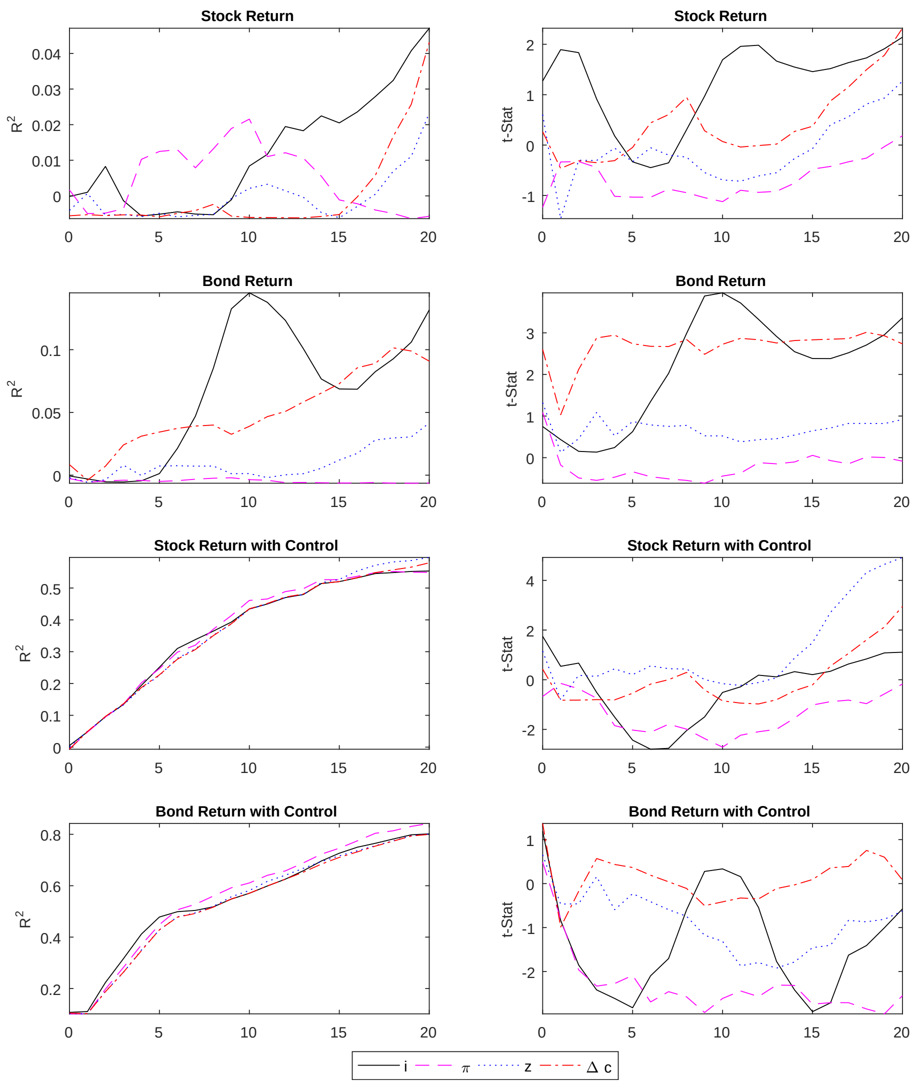


Figure 9: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961QIII to 2008QIII. The dependent variables are cumulative log returns from time t up to $t + 20$, or up to 5 years, for equity (the first and third rows) and nominal bonds (the second and fourth rows). The top two rows are univariate regressions in which the explanatory variables are volatilities of the nominal short rate (i), inflation (π), the output gap (z), and consumption growth (Δc). The bottom two rows are the same regressions with added control variables. In the third row, dividend yield and *cay* are used as controls for equity returns, while in the fourth row, forward rates are used. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Sources: FRED database, CRSP, and Board of Governors of the Federal Reserve System.

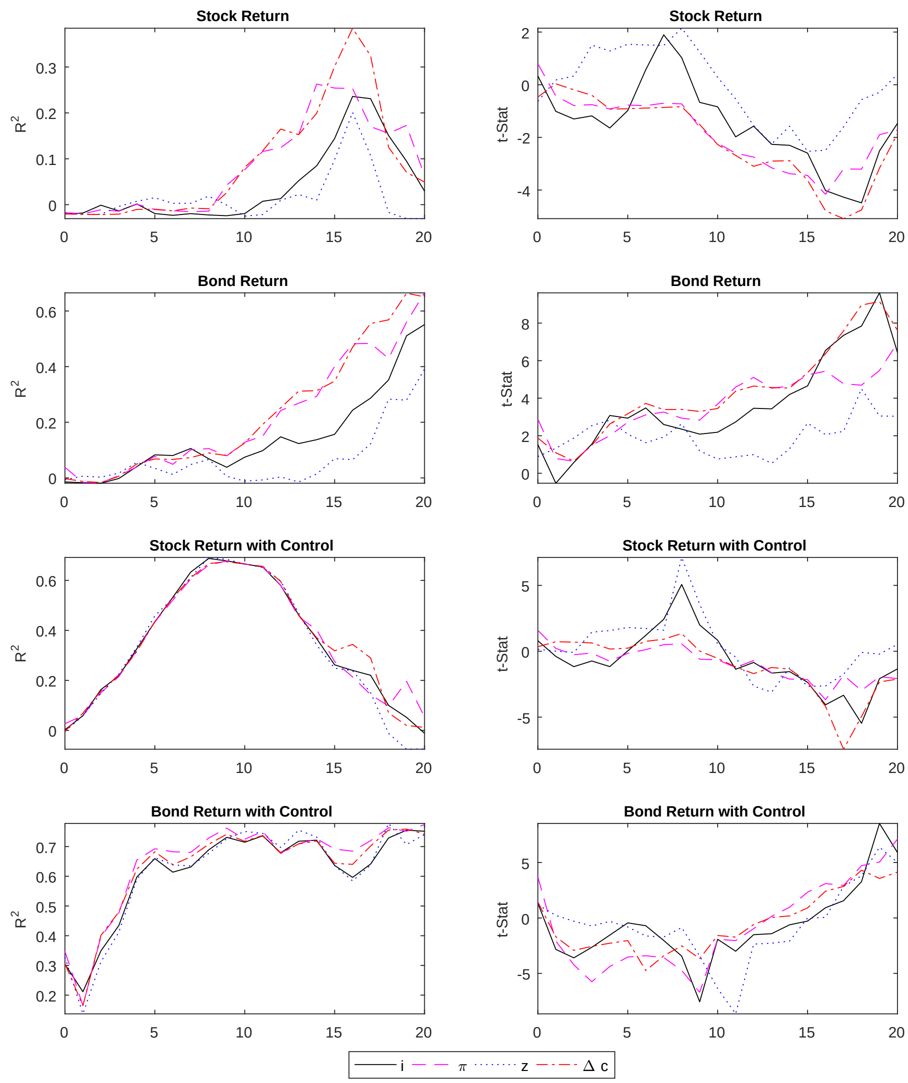


Figure 10: Adjusted R^2 and t-statistics of predictive regressions for the early sample from 1961QIII to 1976QIV. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first and third rows) and nominal bonds (the second and fourth rows). The top two rows are univariate regressions in which the explanatory variables are volatilities of the nominal short rate (i), inflation (π), the output gap (z), and consumption growth (Δc). The bottom two rows are the same regressions with added control variables. In the third row, dividend yield and *cay* are used as controls for equity returns, while in the fourth row, forward rates are used. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Sources: FRED database, CRSP, and Board of Governors of the Federal Reserve System.

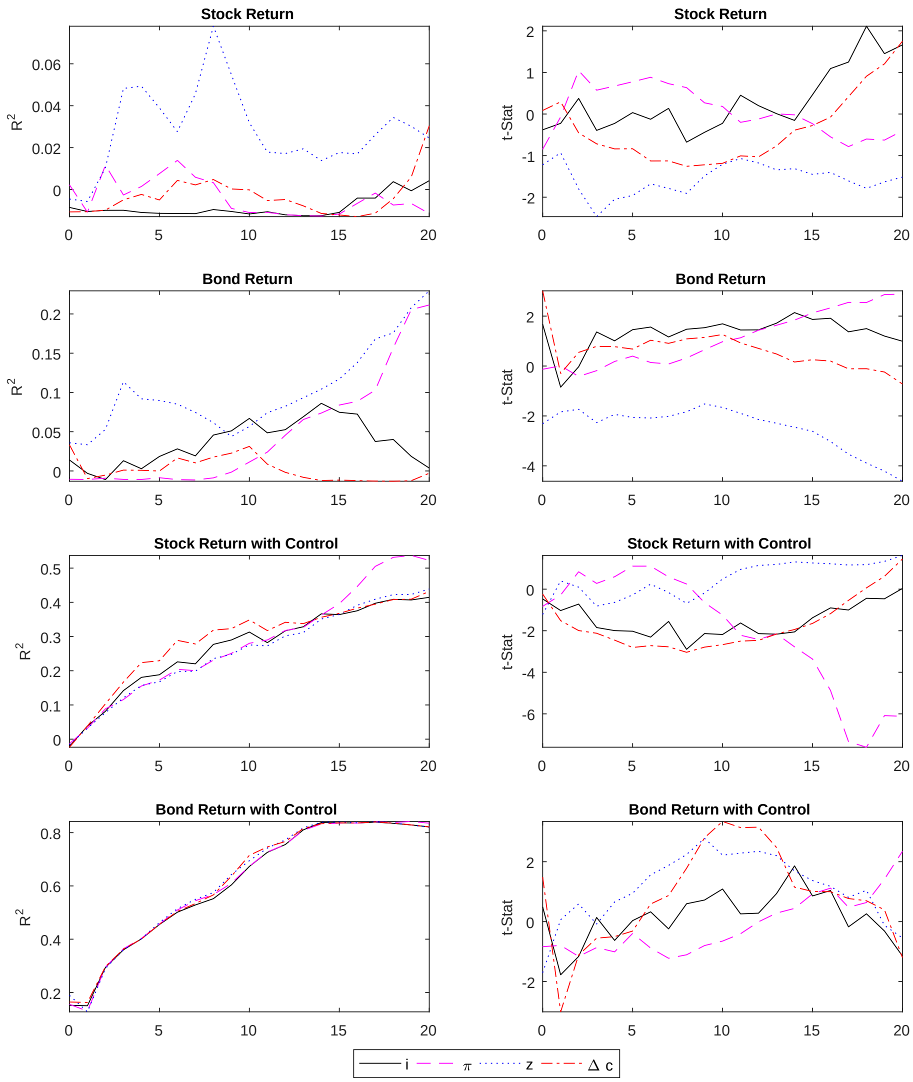


Figure 11: Adjusted R^2 and t-statistics of predictive regressions for the late sample from 1982QI to 2008QIII. The dependent variables are cumulative log returns from time t up to $t+20$, or up to 5 years, for equity (the first and third rows) and nominal bonds (the second and fourth rows). The top two rows are univariate regressions in which the explanatory variables are volatilities of the nominal short rate (i), inflation (π), the output gap (z), and consumption growth (Δc). The bottom two rows are the same regressions with added control variables. In the third row, dividend yield and *cay* are used as controls for equity returns, while in the fourth row, forward rates are used. GMM estimated slope coefficients and Newey-West standard errors are used in reporting the t-statistics. Sources: FRED database, CRSP, and Board of Governors of the Federal Reserve System.

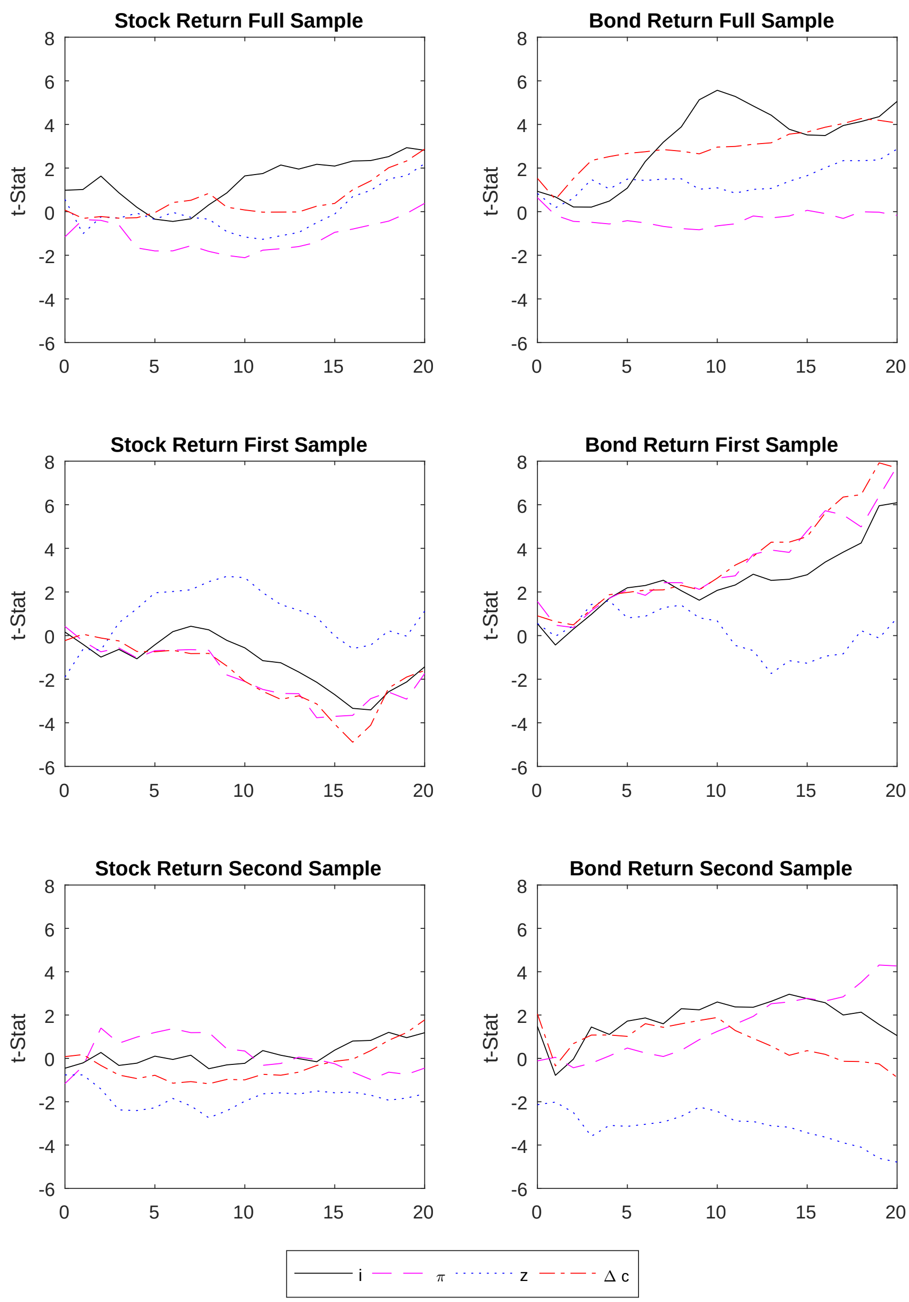
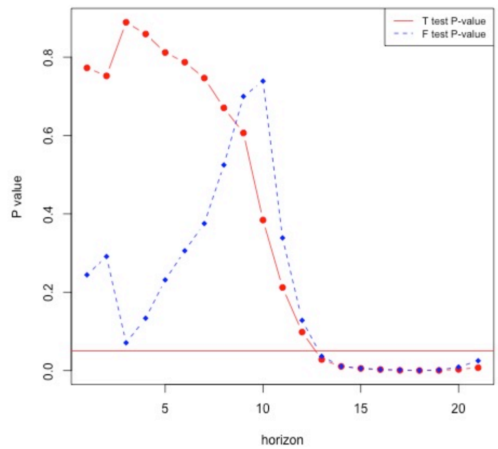
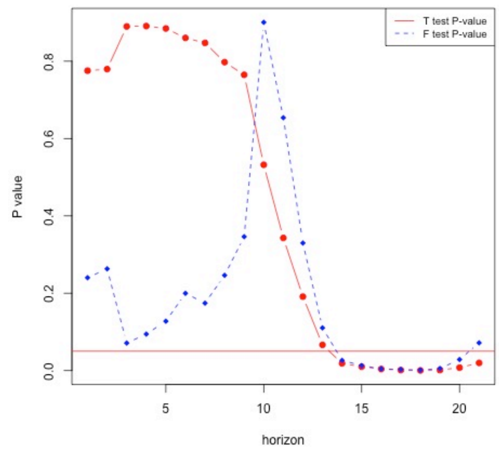


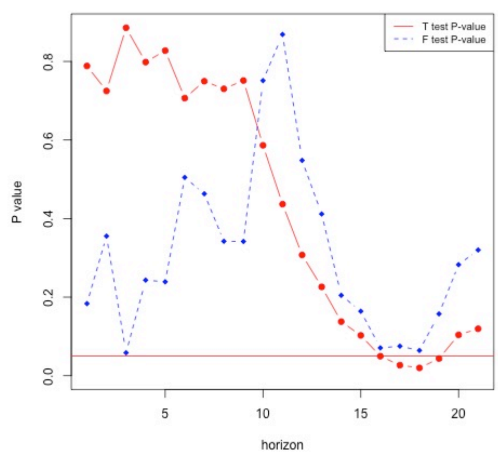
Figure 12: t-statistics using bootstrapped standard errors for univariate stock and bond return predictability regressions with macroeconomic volatility predictors, compared across sample periods. Sources: FRED database, CRSP, and Board of Governors of the Federal Reserve System.



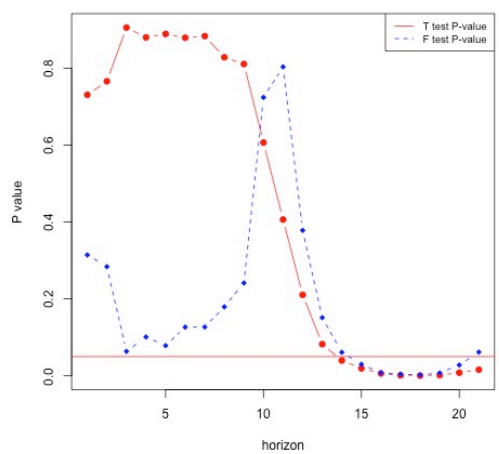
(a) Stock return and consumption growth



(b) Stock return and inflation

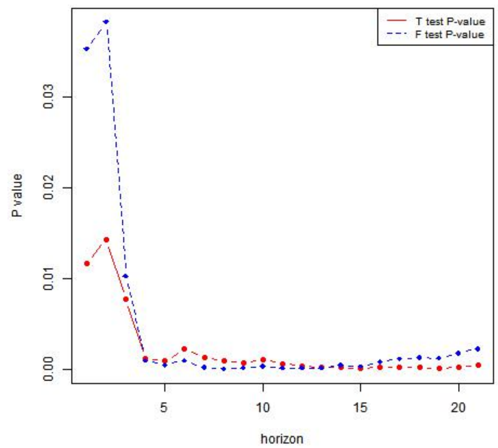


(c) Stock return and output gap

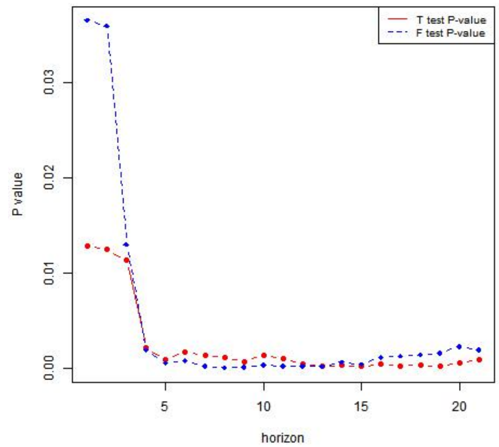


(d) Stock return and fed funds rate

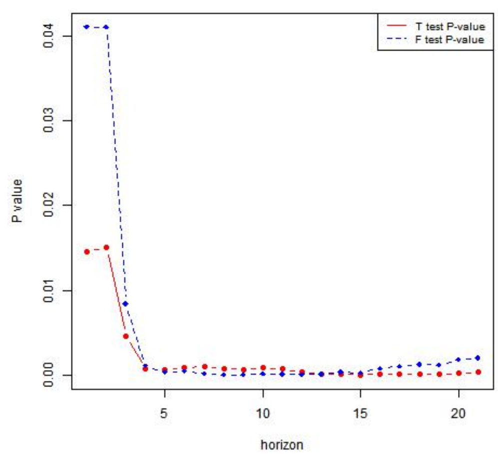
Figure 13: Hypothesis testing using unpaired t test and F test of the residuals from the early and late subsamples. The null hypothesis is the residuals are similar in the two samples. The predictive regressions are for stock returns on conditional volatilities of, in order from subplot (a) to (d), consumption growth, inflation, output gap, and Fed funds rate. The y-axis is the p-value of the test statistic while the x-axis is the return horizon. Sources: FRED database and CRSP.



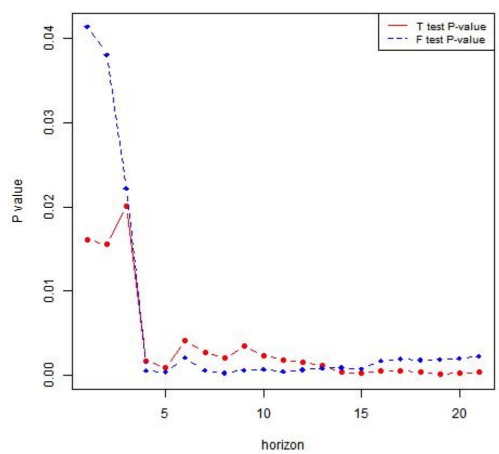
(a) 5Y bond return and consumption growth



(b) 5Y bond return and inflation



(c) 5Y bond return and output gap



(d) 5Y bond return and fed funds rate

Figure 14: Hypothesis testing using unpaired t test and F test of the residuals from the early and late subsamples. The null hypothesis is the residuals are similar in the two samples. The predictive regressions are for bond returns on conditional volatilities of, in order from subplot (a) to (d), consumption growth, inflation, output gap, and Fed funds rate. The y-axis is the p-value of the test statistic while the x-axis is the return horizon. Sources: FRED database and Board of Governors of the Federal Reserve System.

ADDITIONAL MATERIAL

A Dividend Growth and Dividend Yield Predictability

According to Cochrane, return predictability is really not about predicting future returns per se but rather about factors that drive the right-hand-side variables in the Shiller decomposition, namely expected returns and expected dividend growth. In terms of variances, variance of dividend yield is split between future returns and dividend growth:

$$var(dp) = cov(dp_t, \sum_{j=1}^{p} \rho^{j-1} r_{t+j}) - cov(dp_t, \sum_{j=1}^{p} \rho^{j-1} \Delta d_{t+j}) + cov(dp_t, \rho^p dp_{t+p}), \qquad (12)$$

where dp is log dividend yield, r is returns, Δd is log dividend growth, and ρ is the scaling factor. If dividend yields vary at all, it has to come from either the discount rate channel, $cov(dp_t, \sum_{j=1}^{k} \rho^{j-1} r_{t+j})$, or the cash flow channel, $cov(dp_t, \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j})$, or there is an asset bubble if high dividend yield now predicts higher dividend yields in the future.

We have seen how macroeconomic volatilities drive expected returns in the previous section, now we ask if macroeconomic volatilities can affect future dividend yields and expected cash flows to understand which terms in equation 12 are functions of stochastic volatilities. We perform the same full sample and subsample analysis here to discern whether money policy has had any differential impact on dividend yields and dividend growth. We use predictive regressions similar to equation 1:

$$\begin{aligned} dp_{t+p} &= \alpha_p + \beta_p * SV_t^{i,\pi,x,\Delta c} + \epsilon_{p,t}, \\ \Delta d_{t \to t+p} &= \alpha_p + \beta_p * SV_t^{i,\pi,x,\Delta c} + \epsilon_{p,t}, \end{aligned}$$

where $\Delta d_{t \to t+p}$ is the cumulative dividend growth from time t to time $t+p$. Figure 15 presents the regression results in terms of adjusted R^2 (left column) and t-statistics (right column) for the full sample from 1961QIII to 2008QIII. The subplots in the top row are for regressions where dividend yields are used while the subplots in the bottom row are for regressions where dividend growth are used.

For dividend yields predictability in the full sample, stochastic volatilities on inflation and the nominal short term interest rate strongly predict dividend yields both in terms of R^2 and t-statistics across all horizons. The maximal R^2 for inflation stochastic volatility is around 40% 18 quarters out and for interest rate stochastic volatility is around 20% 6 quarters out, both with t-statistics well above 3. In long-horizon regressions beyond eight quarters, output gap stochastic volatility becomes highly significant, and its predictive regressions have high R^2s. Consumption growth stochastic volatility, on the other hand, has no explanatory power on future dividend yields for all horizons. Not only the t-statistics are insignificant, the R^2s are all close to zero. Finally, all slope coefficients in the dividend yield regressions are positive, including the contemporaneous regression when horizon is zero. This has two implications. First, stock prices are low when monetary policy variable volatilities are high. Second, policy variable volatilities generate significant positive covariances between pd_t and pd_{t+p}, potentially leading to asset bubbles.

The bottom two subplots in Figure 15 show the results of the dividend growth predictive regressions. In general, dividend growth is predictable using macroeconomic stochastic volatilities only at long horizons beyond three years. Interest rate and output gap stochastic volatilities are the strongest predictors reaching R^2s of 10% and 15%, respectively, with highly significant t-statistics. However, contrasting the top row of Figure 15 from the bottom row shows that dividend growth rates are not as predictable as dividend yields. The maximal R^2 in the bottom left subplot for any stochastic volatility series is about 15%. However, consumption growth stochastic volatility appears to be a better predictor for dividend growth than dividend yields in the long horizon.

Next, we repeat the same dividend yield and dividend growth predictive regressions in the split samples. Figure 16 summarizes the regression results for the early subsample from 1961QIII to 1976QIV in the same four subplots: adjusted R^2 and t-statistics in columns with dividend yield and dividend growth in rows, in order. For both set of predictive regressions, explanatory power of the macroeconomic stochastic volatilities are weak. The adjusted R^2s reach double digits only on two occasions for dividend yields and never go above 8% for dividend growth. The top and bottom subplots in the right column of Figure 16 show that the coefficient loadings on stochastic volatilities are not displaying statistical significance consistently across prediction horizons to confirm predictability of dividend yields and dividend growth in the early sample.

In the late subsample from 1982QI to 2008QIII, dividend yield predictability is strong while dividend growth predictability is absent. Figure 17 plots the results. For dividend yields, output gap stochastic volatility is the dominate predictor reaching a maximal adjsuted R^2 of close to 40%. Inflation stochastic volatility also performs well, particularly in the longer horizon. Consumption growth and interest rate volatilities do not have predictive power on future dividend yields in the recent subsample. These observations are borne out by the t-statistics to the right: slope coefficients on output gap and inflation stochastic volatilities are consistently significant but otherwise insignificant on consumption growth and interest rate stochastic volatilities. In the bottom row of Figure 17, we again find that dividend growth is essentially unpredictable using macroeconomic volatilities in the 1982QI to 2008QIII sample. Reported adjusted R^2s from the predictive regressions are poor while none of the estimated coefficients are persistently above the 10% significance threshold across horizons.

Over time, dividend yields have become more volatile, yet return predictability has gone down. This combined with the fact that dividend growth is not forecastable, both in the full sample as well as in the two subsamples, tell us that the bubble condition or the covariance between current dividend yield and future dividend yields is playing a larger role. This is confirmed in the predictive regressions as stochastic volatilities on macroeconomic variables, especially the monetary policy variables, generate large R^2s and high t-statistics when future dividend yields are the dependent variables. This feature of the data is particularly salient in our second subsample after the structural break in the late 1970s.

B Model Solution

The model summarized by equations (4)-(9) can be solved by the method of undetermined coefficients guessing the system of linear equations:

$$\begin{aligned}
\pi_t &= \bar{\pi} + \pi_x x_t + \pi_u u_t + \pi_\epsilon \epsilon_t + \pi_v v_t, \\
\Delta z_t &= z_x x_t + z_u u_t + z_\epsilon \epsilon_t + z_v v_t, \\
p_{c,t} &= \bar{p}_c + p_{c,x} x_t + p_{c,u} u_t + p_{c,\epsilon} \epsilon_t + p_{c,v} v_t,
\end{aligned}$$

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

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

where $\eta_c = \frac{\exp(\bar{p}_c)}{1+\exp(\bar{p}_c)}$, and $\bar{\eta_c} = \log(1+\exp(\bar{p}_c)) - \eta_c \bar{p}_c$. The coefficients for the inflation process are:

$$\pi_x = \frac{\phi_{\pi z} z_x}{1-\beta_\pi \phi_x}, \quad \pi_u = \frac{\phi_{\pi z} z_u}{1-\beta_\pi \phi_u}, \quad \pi_\epsilon = \frac{\phi_{\pi z} z_\epsilon + 1}{1-\beta_\pi \phi_\epsilon}, \quad \pi_v = \frac{\phi_{\pi z} z_v}{1-\beta_\pi \phi_v}.$$

The coefficients for the wealth-consumption ratio are:

$$\begin{aligned}
p_{c,x} &= \frac{\left(1-\frac{1}{\psi}\right)(1+z_x\phi_x)}{1-\eta_c\phi_x}, \quad p_{c,u} = \frac{\left(1-\frac{1}{\psi}\right) z_u\phi_u}{1-\eta_c\phi_u}, \quad p_{c,\epsilon} = \frac{\left(1-\frac{1}{\psi}\right) z_\epsilon\phi_\epsilon}{1-\eta_c\phi_\epsilon}, \\
p_{c,v} &= \left(1-\frac{1}{\psi}\right) z_v\phi_v + \eta_c p_{c,v}\phi_v + \frac{1}{2}\theta\Bigg\{ \left(\left(1-\frac{1}{\psi}\right) z_x + \eta_c p_{c,x}\right)^2 \sigma_{xv} \\
&\quad + \left(\left(1-\frac{1}{\psi}\right) z_u + \eta_c p_{c,u}\right)^2 \sigma_{uv} + \left(\left(1-\frac{1}{\psi}\right) z_\epsilon + \eta_c p_{c,\epsilon}\right)^2 \sigma_{\epsilon v} + \left(1-\frac{1}{\psi}\right)^2 \sigma_{cv} \Bigg\} \\
\bar{p}_c &= \log\beta + \left(1-\frac{1}{\psi}\right) u_c + \bar{\eta_c} + \eta_c\bar{p}_c + \frac{1}{2}\theta\Bigg\{ \left(1-\frac{1}{\psi}\right)^2 \bar{\sigma}_c^2 + \left(\left(1-\frac{1}{\psi}\right) z_x + \eta_c p_{c,x}\right)^2 \bar{\sigma}_x^2 \\
&\quad + \left(\left(1-\frac{1}{\psi}\right) z_u + \eta_c p_{c,u}\right)^2 \bar{\sigma}_u^2 + \left(\left(1-\frac{1}{\psi}\right) z_\epsilon + \eta_c p_{c,\epsilon}\right)^2 \bar{\sigma}_\epsilon^2 + \left(\left(1-\frac{1}{\psi}\right) z_v + \eta_c p_{c,v}\right)^2 \bar{\sigma}_v^2 \Bigg\},
\end{aligned}$$

and the coefficients for the process capturing the change in the output gap are:

$$z_x = \frac{\frac{1}{\psi}}{\frac{(\imath_\pi-\phi_x)\phi_{\pi z}}{1-\beta_\pi\phi_x} + \imath_z - \frac{1}{\psi}\phi_x}, \quad z_u = \frac{-1}{\frac{(\imath_\pi-\phi_u)\phi_{\pi z}}{1-\beta_\pi\phi_u} + \imath_z - \frac{1}{\psi}\phi_u}, \quad z_\epsilon = \frac{-\frac{(\imath_\pi-\phi_\epsilon)\phi_{\pi z}}{1-\beta_\pi\phi_\epsilon}}{\frac{(\imath_\pi-\phi_\epsilon)\phi_{\pi z}}{1-\beta_\pi\phi_\epsilon} + \imath_z - \frac{1}{\psi}\phi_\epsilon},$$

$$z_v = -\left(\frac{(\imath_\pi-\phi_v)\phi_{\pi z}}{1-\beta_\pi\phi_v} + \imath_z - \frac{1}{\psi}\phi_v\right)^{-1} \Bigg\{ \frac{1}{2}\theta(1-\theta)\Bigg[\left[\left(1-\frac{1}{\psi}\right) z_x + \eta_c p_{c,x}\right]^2 \sigma_{xv} +$$
$$\left[\left(1-\frac{1}{\psi}\right) z_u + \eta_c p_{c,u}\right]^2 \sigma_{uv} + \left[\left(1-\frac{1}{\psi}\right) z_\epsilon + \eta_c p_{c,\epsilon}\right]^2 \sigma_{\epsilon v} + \left(1-\frac{1}{\psi}\right)^2 \sigma_{cv}\Bigg] +$$

$\frac{1}{2}\Big[\left(\gamma z_x + \pi_x + (1-\theta)\eta_c p_{c,x}\right)^2 \sigma_{xv} + \left(\gamma z_u + \pi_u + (1-\theta)\eta_c p_{c,u}\right)^2 \sigma_{uv} +$

$\left(\gamma z_\epsilon + \pi_\epsilon + (1-\theta)\eta_c p_{c,\epsilon}\right)^2 \sigma_{\epsilon v} + \gamma^2 \sigma_{cv}\Big]\Big\}$

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

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

where

$$\begin{aligned} \Gamma_0 &= -\theta \log \beta + \gamma u_c + (1-\theta)(\bar{\eta}_c + \eta_c \bar{p}_c - \bar{p}_c), \quad \Gamma_x = \frac{1}{\psi}(1 + z_x \phi_x), \\ \Gamma_u &= \frac{1}{\psi} z_u \phi_u, \quad \Gamma_\epsilon = \frac{1}{\psi} z_\epsilon \phi_\epsilon, \quad \Gamma_v = \gamma z_v \phi_v + (1-\theta)(\eta_c p_{c,v} \phi_v - p_{c,v}), \\ \lambda_c &= \gamma, \quad \lambda_x = \gamma z_x + (1-\theta)\eta_c p_{c,x}, \quad \lambda_u = \gamma z_u + (1-\theta)\eta_c p_{c,u}, \\ \lambda_\epsilon &= \gamma z_\epsilon + (1-\theta)\eta_c p_{c,\epsilon}, \quad \lambda_v = \gamma z_v + (1-\theta)\eta_c \; p_{c,v}. \end{aligned}$$

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

$$p_{d,t} = \bar{p}_d + p_{d,x} x_t + p_{d,u} u_t + p_{d,\epsilon} \epsilon_t + p_{d,v} v_t,$$

with coefficients

$\bar{p_d} = -\Gamma_0 + \bar{\eta_d} + \eta_d \bar{p_d} + \mu_d + \frac{1}{2}((\lambda_c - \sigma_{dc})\bar{\sigma_c}^2 + (\lambda_x - \eta_d p_{d,x})^2 \bar{\sigma_x}^2 + (\lambda_u - \eta_d p_{d,u})^2 \bar{\sigma_u}^2 + (\lambda_\epsilon - \eta_d p_{d,\epsilon})^2 \bar{\sigma_\epsilon}^2 + (\lambda_v - \eta_d p_{d,v})^2 \sigma_v^2 + \bar{\sigma_d}^2$

$$p_{d,x} = \frac{\phi_{dc}(1 + z_x \phi_x) - \Gamma_x}{1 - \eta_d \phi_x}, \quad p_{d,u} = \frac{\phi_{dc} z_u \phi_u - \Gamma_u}{1 - \eta_d \phi_u} \quad p_{d,\epsilon} = \frac{\phi_{dc} z_\epsilon \phi_\epsilon - \Gamma_\epsilon}{1 - \eta_d \phi_\epsilon}$$

$p_{d,v} = -\Gamma_v + \phi_{dc} z_v \phi_v + \eta_d p_{d,v} \phi_v + \frac{1}{2}((\lambda_c - \sigma_{dc})\sigma_{cv} + (\lambda_x - \eta_d p_{d,x})^2 \sigma_{xv} + (\lambda_u - \eta_d p_{d,u})^2 \sigma_{uv} + (\lambda_\epsilon - \eta_d p_{d,\epsilon})^2 \sigma_{\epsilon,i} + \sigma_{dv})$

The real risk-free rate is

$$r_t = \bar{r} + r_x x_t + r_u u_t + r_\epsilon \epsilon_t + r_v v_t,$$

where

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

The equity premium can be computed as

$$
\begin{aligned}
-cov_t(m_{t,t+1}, r_{d,t+1}) &= -cov_t(m_{t,t+1}, \eta_d p_{d,t+1} + \Delta d_{t+1}) \\
&= \lambda_c\sigma_{dc}\sigma_{c,t}^2 + \lambda_x\eta_d p_{d,x}\sigma_{x,t}^2 + \lambda_u\eta_d p_{d,u}\sigma_{u,t}^2 \\
&+ \lambda_\epsilon\eta_d p_{d,\epsilon}\sigma_{\epsilon,t}^2 + \lambda_v\eta_d p_{d,v}\sigma_v^2.
\end{aligned}
$$

The one-period nominal interest rate is

$$
i_t = \bar{i} + i_x x_t + i_u u_t + i_\epsilon \epsilon_t + i_v v_t,
$$

where

$$
\begin{aligned}
\bar{i} &= \Gamma_0 + \bar{\pi} - \frac{1}{2}\left(\lambda_c^2\bar{\sigma}_c^2 + (\lambda_x + \pi_x)^2\bar{\sigma}_x^2 + (\lambda_u + \pi_u)^2\bar{\sigma}_u^2 + (\lambda_\epsilon + \pi_\epsilon)^2\bar{\sigma}_\epsilon^2 + (\lambda_v + \pi_v)^2\sigma_v^2\right), \\
i_x &= i_x = \Gamma_x + \pi_x\phi_x, \quad i_u = \Gamma_u + \pi_u\phi_u, \quad i_\epsilon = \Gamma_\epsilon + \pi_\epsilon\phi_\epsilon, \\
i_v &= \Gamma_v + \pi_v\phi_v - \frac{1}{2}\left(\lambda_c^2\sigma_{cv} + (\lambda_x + \pi_x)^2\sigma_{xv} + (\lambda_u + \pi_u)^2\sigma_{uv} + (\lambda_\epsilon + \pi_\epsilon)^2\sigma_{\epsilon v}\right).
\end{aligned}
$$

Nominal bond yields are given by

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

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

$$
\begin{aligned}
\mathcal{A}_n &= \mathcal{A}_{n-1} + \Gamma_0 - \frac{1}{2}[\lambda_c^2\bar{\sigma}_c^2 + (\lambda_x + \mathcal{B}_{x,n-1})^2\bar{\sigma}_x^2 + (\lambda_u + \mathcal{B}_{u,n-1})^2\bar{\sigma}_u^2 \\
&+ (\lambda_\epsilon + \mathcal{B}_{\epsilon,n-1})^2\bar{\sigma}_\epsilon^2 + (\lambda_v + \mathcal{B}_{v,n-1})^2\sigma_v^2], \\
\mathcal{B}_{x,n} &= \Gamma_x + \mathcal{B}_{x,n-1}\phi_x, \\
\mathcal{B}_{u,n} &= \Gamma_u + \mathcal{B}_{u,n-1}\phi_u, \\
\mathcal{B}_{\epsilon,n} &= \Gamma_\epsilon + \mathcal{B}_{\epsilon,n-1}\phi_\epsilon, \\
\mathcal{B}_{v,n} &= \Gamma_v + \mathcal{B}_{v,n-1}\phi_v - \frac{1}{2}[\lambda_c^2\sigma_{cv} + (\lambda_x + \mathcal{B}_{x,n-1})^2\sigma_{xv} + (\lambda_u + \mathcal{B}_{u,n-1})^2\sigma_{uv} \\
&+ (\lambda_\epsilon + \mathcal{B}_{\epsilon,n-1})^2\sigma_{\epsilon,v}].
\end{aligned}
$$

C Tables and Figures - Additional Material

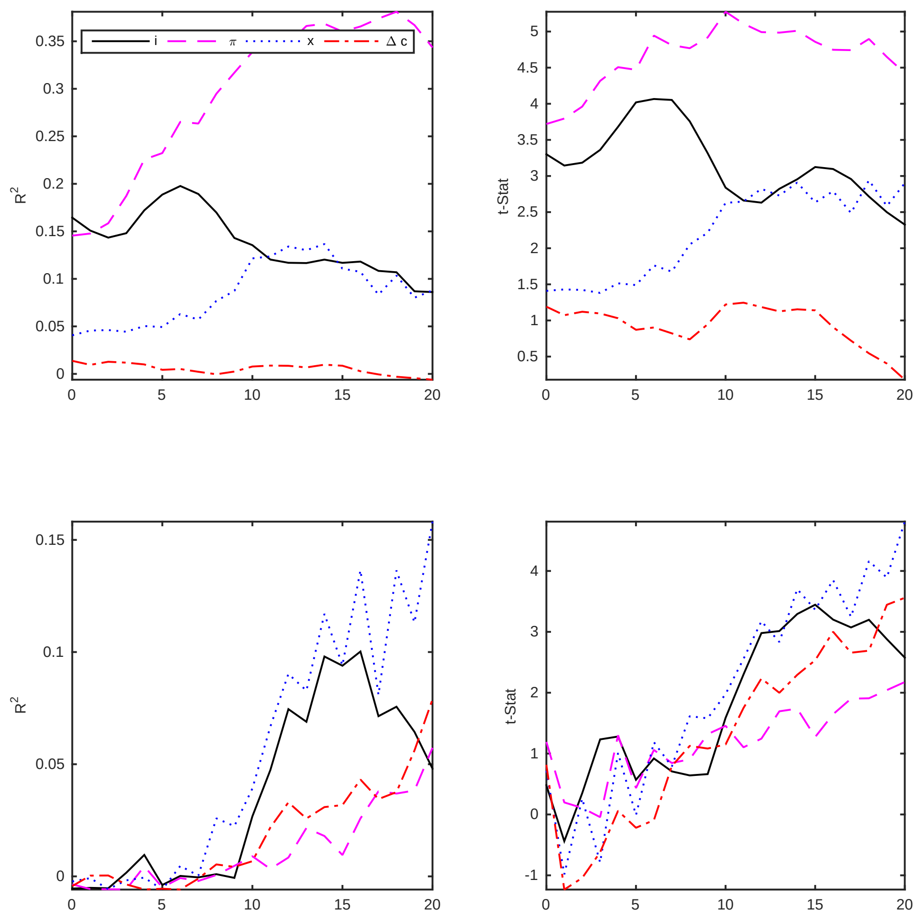


Figure 15: Adjusted R^2 and t-statistics of predictive regressions for the full sample from 1961QIII to 2008QIII. The dependent variables are cumulative dividend yields (top row) and dividend growth (bottom row) from time t up to $t + 20$, or up to 5 years, for equity. The explanatory variables are volatilities of the nominal short rate (i), inflation (π), the output gap (x), and consumption growth (Δc). Sources: FRED database and CRSP.

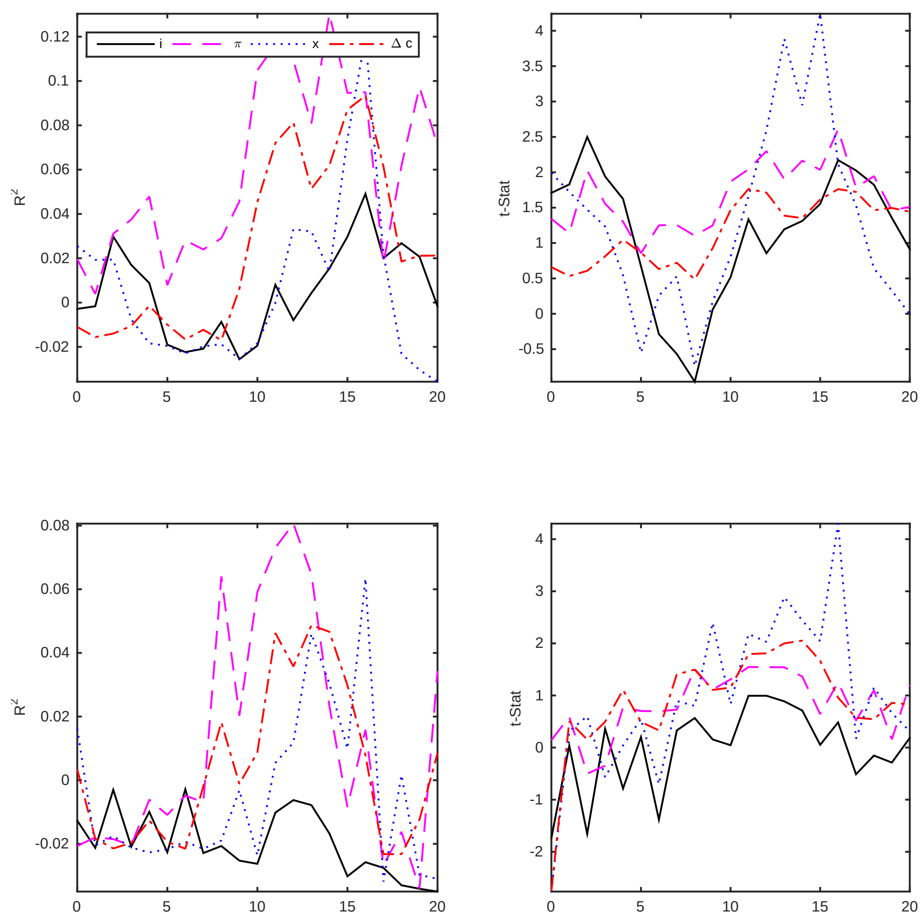


Figure 16: Adjusted R^2 and t-statistics of predictive regressions for the early sample from 1961QIII to 1976QIV. The dependent variables are cumulative dividend yields (top row) and dividend growth (bottom row) from time t up to $t+20$, or up to 5 years, for equity. The explanatory variables are volatilities of the nominal short rate (i), inflation (π), the output gap (x), and consumption growth (Δc). Sources: FRED database and CRSP.

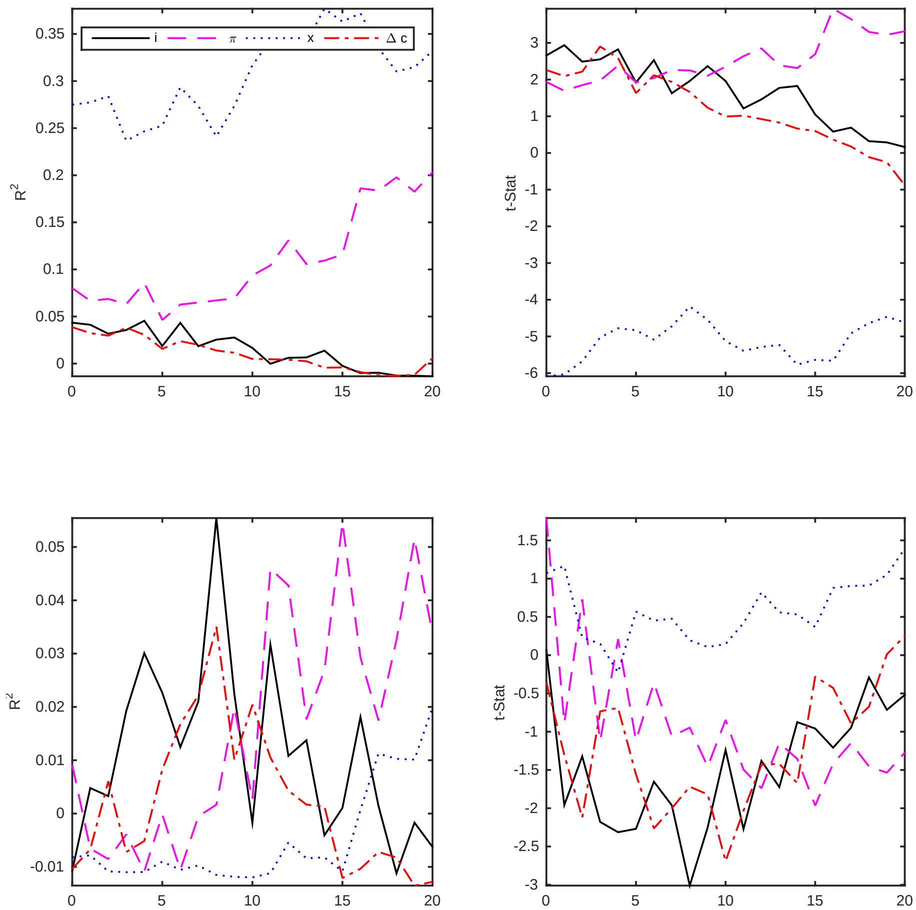


Figure 17: Adjusted R^2 and t-statistics of predictive regressions for the late sample from 1982QI to 2008QIII. The dependent variables are cumulative dividend yields (top row) and dividend growth (bottom row) from time t up to $t+20$, or up to 5 years, for equity. The explanatory variables are volatilities of the nominal short rate (i), inflation (π), the output gap (x), and consumption growth (Δc). Sources: FRED database and CRSP.