Macroeconomic Risks and Asset Pricing: Evidence from a Dynamic Stochastic General Equilibrium Model *

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Abstract

We study the relation between macroeconomic fundamentals and asset pricing through the lens of a state of the art dynamic stochastic general equilibrium (DSGE) model considered in Christiano, Trabandt and Walentin (2011). We provide a full-information Bayesian estimation of the model using macro variables and extract three fundamental shocks to the economy through the model: neutral technology (NT) shock, investment-specific technological (IST) shock, and monetary policy (MP) shock. While it has been shown that the DSGE model matches a wide range of macroeconomic variables well, we are the first to empirically examine the asset pricing implication of the model. The three shocks explains 49% of the cross-sectional return variations among 10 size, 10 book-to-market, and 10 asset growth portfolios and the pricing error is statically indifferent from zero. The risk premiums associated with IST, MP, and NT shocks are 1.35%, -0.35%, and 0.12% per quarter, respectively, with the first two being statistically significant at 1% level and the third one at 10% level. Moreover, the three shocks have significant and robust predictive power of the returns of a wide range of financial assets, which include stocks, long-term corporate and government bonds. Compared to some well-known predictors in the literature, such as *cay* of Lettau and Ludvigson (2001) and *output gap* of Cooper and Priestley (2009), the three shocks are obtained from a structural model, closer to economic fundamentals, represent more exogenous shocks to the economy, and have stronger predictive power of the returns of not only stocks but also other asset classes. Our results show that DSGE models, which have been successful in modeling macroeconomic dynamics, have great potential in capturing asset price dynamics as well.

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1 Introduction

One of the key issues in asset pricing is to understand the economic fundamentals that drive the fluctuations of asset prices. Modern finance theories on asset pricing, however, have mainly focused on the relative pricing of different financial securities. For example, the well-known Black-Scholes-Merton option pricing model considers the relative pricing of option and stock while taking the underlying stock price as given. The celebrated Capital Asset Pricing Model (CAPM) relates individual stock returns to market returns without specifying the economic forces that drive market returns. Modern dynamic term structure models also mainly focus on the relative pricing of bonds across the yield curve. These models tend to assume that the yield curve is driven by some latent state variables without explicitly modeling the economic nature of these variables.

Increasing attention has been paid in the literature to relate asset prices to economic fundamentals as evidenced by the rapid growth of the macro finance literature. For example, the macro term structure literature has been trying to relate term structure dynamics to macro fundamentals. By incorporating the Taylor rule into traditional term structure models, several studies have shown that inflation and output gap can explain a significant portion of the fluctuations of bond yields. The investment based literature has also tried to relate equity returns to firm fundamentals, thus giving economic meaning to empirical based factors (such as HML and SMB) for equity returns. Current attempts to connect macro variables with asset prices, however, are typically based on partial equilibrium analysis. Without a well specified general equilibrium model, it is not clear that the exogenously specified pricing kernels in these "reduced-form" models are consistent with general equilibrium. It is also difficult to identify any causal relations among government policies, macro variables, and asset prices. Given that financial assets are claims on real assets, explicit general equilibrium modeling of the whole economy might help to better understand the economic forces that drive asset prices.

The New Keynesian Dynamic Stochastic General Equilibrium (DSGE) models offer such a framework to understand the link between asset prices and economic fundamentals. DSGE models have become a dominant modeling framework in macroeconomics and have been widely used by both academics and central banks around the world for policy analysis, (see, e.g., **?** and Gali and Gertler (2007)). Under the sticky price equilibrium of these models, monetary policy is not neutral and has important impacts on the real activities of the economy and direct implications for the prices of financial assets. However, most existing studies on DSGE models in the macroeconomic literature, such as **?**, **?** , and **?**, have mainly focused on the real sector and ignored the financial sector. The recent global financial crisis has highlighted the importance of the financial sector for the stability of the global economy. A good DSGE model should be able to capture the financial sector and consequently asset prices well. Therefore, financial prices provide an alternative perspective to examine potential shortcomings of DSGE models: If they make counter factual predictions on financial prices, then one should be careful in using them for policy analysis. Since financial prices are forward looking and contain market expectations for future economic activities, we can also better identify model parameters and policy shocks by incorporating financial prices in the estimation of DSGE models.

In this paper, we study the link between macroeconomic fundamentals and asset pricing through the lens of New Keynesian DSGE models. In particular, we study whether fundamental economic shocks considered in these models have any explanatory power of the returns of a wide range of financial assets, which include aggregate stock market index and long-term corporate and government bonds. Given that financial assets represent claims on real productive assets, important drivers of economic growth and business cycle should also affect the fluctuations of financial asset returns. For example, total factor productivity represents the overall efficiency of capital and labor in producing goods and services, while investment-specific technological shock represents the efficiency of machines and equipments. Non-neutral monetary policy also has significant impact on real economic activities. Therefore, at least theoretically there should be close connections between these macroeconomic factors and financial asset returns.

Our analysis is based on a state of the art DSGE model considered in Christiano, Trabandt and Walentin (2011) (CTW), which includes all the major ingredients of DSGE models. CTW have shown that this model matches a wide range of macroeconomic variables very well. In this paper, we provide one of the first studies that examines the ability of this DSGE model in explaining aggregate stock market returns. Our paper makes several important contributions to the macro literature on DSGE models as well as the finance literature on asset pricing.

First, we develop full-information Bayesian Markov Chain Monte Carlo (MCMC) methods for estimating DSGE models using macroeconomic variables. Whereas the Bayesian moment matching methods of CTW essentially match the unconditional moments of the macro variables, our full-information Bayesian MCMC methods fully exploit the conditional information contained in the likelihood function of the macro data. As a result, our methods provide more efficient estimation of model parameters. More important, our MCMC methods make it possible to back out the latent shocks to the economy in DSGE models. In contrast, the Bayesian moment matching methods cannot back out the latent shocks because they can only match the long-run average features of the data.

Second, we estimate the DSGE model of CTW using our full-information Bayesian MCMC methods based on macroeconomic variables only. We obtain reasonable estimates of model parameters and confirm the findings of CTW that the DSGE model can match a wide range of macro variables well. In addition, we back out the three fundamental shocks to the economy in the DSGE model, namely the neutral technology (NT) shock, the investment-specific technological (IST) shock, and the monetary policy (MP) shock.

Third, we explore the cross-sectional explanatory power of the three shocks on asset returns using 10 size, 10 book-to-market, and 10 asset growth portfolios. We form mimicking portfolios for the three latent shocks, labeled as risk factors f_{NT}, f_{IST}, and f_{MP}, following **?** and **?**. We then estimate the risk premiums of the three risk factors using the two-step **?** cross-sectional regressions based on the aforementioned 30 test portfolios. Our results show that the three risk factors explain

49% of the cross-sectional return differences among the 30 test portfolios and the unexplained part is statistically indifferent from zero (magnitude and t-statistic of α are 0.77% per quarter and 1.04, respectively). The estimated risk premiums of f_{IST} and f_{MP} are 1.35% and -0.35% per quarter, both significant at 1% level. The risk premium of f_{NT} is 0.12% per quarter but only significant at 10% level. As for factor loadings, 28 out of 30 (all 30) loadings of f_{IST} and all 30 loadings of f_{MP} are significantly different from zero at 1% (10%) level for the 30 test portfolios. However, only 1 out of 30 loadings of f_{NT} is significantly different from zero at 10% level. Moreover, the three risk factors explain 140%, 60%, and 55% of the average return differences between extreme portfolios sorted on size, book-to-market, and asset growth, respectively.

Finally, we examine the predictive power of the three extracted shocks of the returns of the aggregate stock, and long-term corporate and government bonds. We regress the returns of the CRSP value-weighted index, and the Ibbotson index of long-term corporate and government bonds on the NT, IST, and MP shocks. The whole sample period is from the first quarter of 1966 to the third quarter of 2010. We use the three shocks to forecast future one-month, one-quarter, and one-year returns of stock, long-term corporate and government bonds. In general, we find all three shocks have strong predictive power of future stock, corporate and government returns. Welch and Goyal (2007) have shown that predictability of stock returns tend to be sensitive to sample period used. To test the robustness of our results, we change the starting date of the sample period to the first quarter of 1970 and 1975 and obtain very similar results. We find that our three shock variables have much stronger and more robust predictive power than some well-known macro predictors, such as *cay* and *gap*, and financial predictors, such as dividend ratio, earnings to price ratio, default spread, and term spread. More important, while some variables have predictive power for certain asset classes, our three shock variables have strong predictive power for ALL assets!

We also examine the predictive power of the three shocks of some well-known predictive variables that have been studied in the literature, such as the *cay* factor of Lettau and Ludvigson

(2001) and output gap (*gap*) of Cooper and Priestley (2009). We find that the three shock variables can explain more than 40% of the variations of *cay* and about 4% of *gap*.

Our result is a testament of the power of the DSGE approach. Given that we estimate the DSGE model using only macro data, it is amazing that the three shocks extracted from the model have such strong predictive power of a wide range of financial assets. The three shocks have important advantages over other predictive variables considered in the literature. First, they are derived from a structural economic model and therefore have clear economic meaning. Second, they represent more fundamental forces in the economy. In contrast, *cay* and *gap* are derived rather than fundamental variables. Third, the three shocks represent more exogenous forces to the economy. Finally, the most important advantage of our approach is that it shows that the DSGE approach captures important elements of the economy such that the shocks extracted from the model can predict asset returns even out of sample. Therefore, it highlights the possibility of integrating macroeconomics and asset pricing under an unified modeling framework.

The rest of the paper is organized as follows. Section II introduces the DSGE model. Section III discusses the full-information Bayesian estimation methods and model implications on asset prices. Section IV and V empirically examine the asset pricing implications at the cross section and at the time series, respectively. Section VI concludes.

2 The Model

The DSGE model that we estimate is taken from CTW. The modeled economy contains a perfectly competitive final goods market, a monopolistic competitive intermediate goods market, households who derive utility from final goods consumption and disutility from supplying labor to production. There are **?** type of nominal price rigidities and wage rigidities in the intermediate goods market. Government consumes a fixed fraction of GDP very period and the monetary authority set the nominal interest rate according to a Taylor rule. There are three exogenous shocks in the economy:

total factor productivity shocks, investment-specific technological shocks, and monetary policy shocks. CTW show that the model matches vey well an important set of macroeconomic variables including: changes in relative prices of investment, real per hour GDP growth rate, unemployment rate, capacity utilization, average weekly hours, consumption-to-GDP ratio, investment-to-GDP ratio, job vacancies, job separation rate, job finding rate, weekly hours per labor force, Federal Funds Rates. Next, we present the model in details.

2.1 Production sector

There are two industries in the production sector, final goods industry and intermediate goods industry. The production of the final consumption goods uses a continuum of intermediate goods, indexed by $i \in [0, 1]$ via the Dixit-Stiglitz aggregator

$$Y_t = \left[\int_0^1 Y_{i,t}^{\frac{1}{\lambda_f}} \, di \right]^{\lambda_f} , \quad \lambda_f > 1 , \tag{1}$$

where Y_t is the output of final goods, $Y_{i,t}$ is the amount of intermediate goods i used in the final good production, which in equilibrium equals the output of intermediate goods i, and λ_f measures the substitutability among different intermediate goods. The larger λ is, the more substitutable the intermediate goods are. Since the final goods industry is perfectly competitive, profit maximization leads to the demand function for intermediate goods i:

$$Y_{i,t} = Y_t \left(\frac{P_{i,t}}{P_t} \right)^{\frac{\lambda_f}{\lambda_f - 1}} , \tag{2}$$

where P_t is the nominal price of the final consumption goods and P_{it} is the nominal price of intermediate goods i. It can be shown that goods prices satisfy the following relation:

$$P_t = \left(\int_0^1 P_{i,t}^{-\frac{1}{\lambda_f - 1}} di \right)^{-(\lambda_f - 1)} . \tag{3}$$

The production of intermediate goods i employs both capital and labor via the following homogenous production technology

$$Y_{i,t} = (z_t H_{i,t})^{1-\alpha} K_{i,t}^{\alpha} - z_t^+ \varphi \,, \tag{4}$$

where z_t is the neutral technology shock, $H_{i,t}$ and $K_{i,t}$ are the labor service and capital service, respectively, employed by firm i, α is the capital share of output, and φ is the fixed production cost. Finally, z_t^+ is defined as

$$z_t^+ = \Psi_t^{\frac{\alpha}{1-\alpha}} z_t \,,$$

where Ψ_t is the investment-specific technology shock, measured as the relative price of consumption goods to investment goods. Assume that the neutral technology shock z_t and Ψ_t evolve as follows:

$$\mu_{z,t} = \mu_z + \rho_z \mu_{z,t-1} + \sigma_z e_t^z \,, \quad \text{where } \mu_{z,t} = \Delta \log z_t \,,\, e_t^z \sim \text{IID}\mathcal{N}(0,1) \,, \tag{5}$$

$$\mu_{\psi,t} = \mu_\psi + \rho_\psi \mu_{\psi,t-1} + \sigma_\psi e_t^\psi \,, \quad \text{where } \mu_{\psi,t} = \Delta \log \Psi_t \,,\, e_t^\psi \sim \text{IID}\mathcal{N}(0,1) \,. \tag{6}$$

The intermediate goods industry is assumed to have no entry and exit, which is ensured by choosing a fixed cost ψ that brings zero profits to the intermediate goods producers.

Intermediate goods producer i rents capital service K_{it} from households and its net profit at period t is given by

$$P_{it} Y_{it} - r_t^K K_{it} - W_t H_{it} \,.$$

The producer takes the rent of capital service r_t^K and wage rate W_t as given but has market power to set the price of its goods in a **?** staggered price setting to maximize its profits. With probability

ξ_p, producer i cannot reoptimize its price and has to set its price according to the following rule,

$$P_{i,t} = \pi\, P_{i,t-1}$$

and with probability $1 - \xi_p$, producer i sets price $P_{i,t}$ to maximize its profits, i.e.,

$$\max_{\{P_{i,t}\}} \; \mathbb{E}_t \sum_{\tau=0}^{\infty} \left(\xi_p\, \beta\right)^{\tau} \nu_{t+\tau} \left[P_{i,t} Y_{i,t+\tau\,|\,t} - W_{t+\tau} H_{t+\tau\,|\,t}\right] \tag{7}$$

subject to the demand function in equation (2). In the above objective function, $Y_{i,t+\tau\,|\,t}$ and $H_{t+\tau\,|\,t}$ refer to the output and labor hiring, respectively, by producer i at time $t+\tau$ if the last time when price P_i is reoptimized is period t.

2.2 Households

Following CTW, we assume that there is a continuum of differentiated labor types indexed with j and uniformly distributed between zero and one. A typical household has infinite many members covering all the labor types. It is assume that a household's consumption decision is made based on utilitarian basis. That is, every household member consumes the same amount consumption goods even though they might have different status of employment. CTW show that a representative household's life-long utility can be written as

$$\sum_{t=0}^{\infty} \beta^t \left[\log\left(C_t - b\, C_{t-1}\right) - A_L \int_0^1 \frac{h_{jt}^{1+\phi}}{1+\phi}\right], \tag{8}$$

subject to the budget constraint

$$P_t \left(C_t + \frac{I_t}{\Psi_t}\right) + B_{t+1} + P_t P_{k',t} \Delta_t \leq \int_0^1 W_{jt} h_{jt}\, dj + X_t^K \bar{K}_t + R_{t-1} B_t \tag{9}$$

for $t = 0, 1, \cdots, \infty$. Here, h_{jt} is the number of household members with labor type j who are employed, B_t is the nominal bond holdings purchased by household at $t-1$, $P_{k',t}$ is the market price of one unit capital stock, X_t^K is the net cash payment to the household by renting out capital $\bar{K}_t$, given by

$$X_t^K = P_t \left[u_t \, r_t^K - \frac{a(u_t)}{\Psi_t} \right] .$$

The wage rate of labor type j is determined by a monopoly union who represents all j-type workers and households take the wage rate of each labor type as given.

Households own the economy's physical capital $\bar{K}$. The amount of capital service K_t available for production is given by

$$K_t = u_t \, \bar{K}_t \,,$$

where u_t is the utilization rate of physical capital and utilization incurs a maintenance cost

$$a(u) = b \, \sigma_a \, u^2/2 + b(1 - \sigma_a) \, u + b \, (\sigma_a \, /2 - 1) \; . \tag{10}$$

where b and σ_a are constants and chosen such that steady state utilization rate is one and at steady state $a(u = 1) = 0$. Note that the maintenance cost $a(u)$ is measured in terms of capital goods, whose relative price to consumption goods is $1/\Phi_t$. A representative household accumulates capital stock according to the following rule:

$$\bar{K}_{t+1} = (1 - \delta) \, \bar{K}_t + F(I_t, I_{t-1}) + \Delta_t \,,$$

where Δ_t is the capital stock purchased by the representative household and equals zero in equilibrium because all households are identical. Here, $F(I_t, I_{t-1})$ is the investment adjustment cost, defined as

$$F(I_t, I_{t-1}) = \left(1 - S\left(\frac{I_t}{I_{t-1}} \right) \right) I_t$$

and

$$S(x_t) = \frac{1}{2}\left\{\exp\left[\sigma_s\left(x_t - \exp(\mu_z^+ + \mu_\psi)\right)\right] + \exp\left[-\sigma_s\left(x_t - \exp(\mu_z^+ + \mu_\psi)\right)\right] - 2\right\} ,$$

where $x_t = I_t/I_{t-1}$ and $\exp(\mu_z^+ + \mu_\psi)$ is the steady state growth rate of investment. The parameter σ_s is chosen such that at steady state $S(\exp(\mu_z^+ + \mu_\psi)) = 0$ and $S'(\exp(\mu_z^+ + \mu_\psi)) = 0$. Note that investment I_t is measured in terms of capital goods. The consumption goods market clearing is then given by

$$Y_t = C_t + G_t + \tilde{I}_t$$

where G_t is government spending and $\tilde{I}$ is investment measured in consumption goods, which also includes the capital maintenance cost $a(u_t)$, i.e.,

$$\tilde{I} = \frac{I_t + u(a_t)}{\Phi_t} .$$

2.3 Labor unions

There are labor contractors who hires all types of labor through labor unions and produce a homogenous labor service H_t, according to the following production function

$$H_t = \left[\int_0^1 h_{jt}^{\frac{1}{\lambda_w}} \, dj\right]^{\lambda_w} , \quad \lambda_w > 1 , \tag{11}$$

where λ_w measures the elasticity of substitution among different labor types. The intermediate goods producers employ the homogenous labor service for production. Labor contractors are perfectly competitive, whose profit maximization leads to the demand function for labor type i

$$h_{jt} = H_t \left(\frac{W_{jt}}{W_t}\right)^{\frac{-\lambda_w}{\lambda_w - 1}} \tag{12}$$

It is easy to show that wages satisfy the following relation:

$$W_t = \left(\int_0^1 W_{j,t}^{-\frac{1}{\lambda_w - 1}} dj \right)^{-(\lambda_w - 1)}, \tag{13}$$

where $W_{j,t}$ is the wage of labor type j and W_t is the wage of the homogenous labor service.

Assume that labor unions face the same **?** type of wage rigidities. Each period, with probability ξ_w, labor union j cannot reoptimize the wage rate of labor type j and has to set the wage rate according to the following rule

$$W_{jt+1} = \pi_t \mu_{z^+}$$

and with probability $1 - \xi_w$, labor union j chooses W_{jt} to maximize households' utility

$$\mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta \xi_w)^\tau \left[\nu_{t+\tau} W_{jt} h_{t+\tau\,|\,t} - A_L \frac{h_{jt+\tau\,|\,t}^{1+\phi}}{1+\phi} \right] \tag{14}$$

subject to the demand curve for labor type j in equation (12). Here, $\nu_{t+\tau}$ is the marginal utility of one $h_{jt+\tau\,|\,t}$ is the supply of type j labor at period $t + \tau$ if the last time that labor union j reoptimizes wage rate W_{jt} is period t.

2.4 Fiscal and Monetary Authorities

Following CTW, fiscal authority in the model simply transfers a fixed fraction g of output as government spending, i.e.,

$$G_t = g\, Y_t\,.$$

Monetary authority sets the level of a short-term nominal interest rate according to the following Taylor rule

$$\log\left(\frac{R_t}{R}\right) = \rho_R \log\left(\frac{R_{t-1}}{R}\right) + (1 - \rho_R) \left[\rho_\pi \log\left(\frac{\pi_t}{\pi}\right) + \rho_y \log\left(\frac{Y_t}{Y}\right) \right] + V_t. \tag{15}$$

where R_t is the short-term interest rate, R, π, and Y are steady state values for interest rate, inflation, and output, and V_t is the monetary policy shock, which follows the process

$$V_t = \rho_V V_{t-1} + \sigma_V e_t^V , \tag{16}$$

with $e_V \sim \text{IID}\mathcal{N}(0, 1)$.

2.5 Model Implications on Asset Prices

The real price of a claim on dividends paid by producers $\{D_{t+s}\}_{s=0}^{\infty}$ is given by

$$S_{D,t} = \mathbb{E}_t \left[\sum_{s=1}^{\infty} M_{t,t+s} D_{t+s} \right] \tag{17}$$

and

$$D_t = Y_t - W_t H_t - r_t^k K_t .$$

The one-period real return of this claim is

$$R_{D,t+1} = \frac{D_{t+1} + S_{D,t+1}}{S_{D,t}} = \frac{D_{t+1}}{D_t} \left(\frac{1 + P_{D,t+1}}{P_{D,t}} \right) , \tag{18}$$

where $P_{D,t}$ is the cash flow-price ratio, defined as $P_{D,t} \equiv \frac{S_{D,t}}{D_t}$.

We study the asset pricing implications of the model through impulse response functions to the three latent shocks. Figure 2 plots the impulse response functions to a one-standard deviation positive NT shock for consumption growth (Δc), stochastic discount factor (M), dividend growth (Δd), price-dividend ratio (P_D), excess stock return (R_D), and expected stock return of next period ($E(R_D)$). A positive shock on the growth rate of neutral technology level leads to higher consumption growth rate and lower stochastic discount factor. The growth rate of dividend claims goes up but quickly reverts back. The price-dividend ratio goes up and stays at a higher value.

Both current period realized excess return and expected next period excess return on dividend claims goes up. However, the change in current period return is an order of magnitude larger than that in expected next period return. Except for price-dividend ratio, all variables gradually revert back to the original values.

Figure 3 plots the impulse response functions to a one-standard deviation positive IST shock for the same set of variables. A positive IST shock leads to lower price of capital goods relative to consumption goods and makes per unit of investment in terms of consumption goods more productive. The qualitative consequences of a positive IST shock are the same as those of a positive NT shock, consistent with our intuition.

Finally, Figure 4 plots the impulse response functions to a one-standard deviation positive MP shock for the same set of variables. A positive MP shock leads to higher nominal interest rate. Due to price and wage rigidities, the increase in nominal interest rate cannot be completely absorbed by inflation and leads to a higher real interest rate. Consequently, the economy contracts. Figure 4 shows that consumption growth goes down, (real) stochastic discount factor goes up, dividend growth goes down and price-dividend ratio goes down. Consistent with what **?** find, contemporaneous return goes down. The model predicts that expected next period excess return also goes down, but with a magnitude around 20 times smaller than the drop in contemporaneous return.

To summarize, the above impulse response functions show that a positive NT shock and/or a positive IST leads to higher contemporaneous return and predicts higher future expected return and a positive MP shock leads to lower contemporaneous return and predicts lower future return. However, the predictive powers of the three latent shocks are very marginal and most of the variations in return come from contemporaneous shocks.

It worth mentioning that the positive risk premium of IST shocks implied by our model are opposite of what **?** predicts. A positive IST shock in **?** leads to more capital input and higher output in capital goods production sector, which, due to the predetermined total capital stock, is accompanied by lower capital input and lower output in consumption. Therefore, a positive IST shock leads to lower consumption growth and hence negative risk premium. Even though we do not model capital goods production sector explicitly, the resource constraint between consumption and capital goods is the same. The reason that a positive IST shock leads to higher consumption growth in our model is due to the variable capital utilization, which is absent in **?**. Even though more capital stock is devoted to producing capital goods after a positive IST shock, consumption goods producers increase the utilization rate of capital to achieve a higher consumption level. Consistent with our finding, the utilization channel is shown to be critical for generating positive IST risk premium in **?**, who have a similar model setup as **?** but with variable capital utilization. The positive relation between IST shock and consumption is also consistent with procyclical capital utilization rate found in the data. Next, we first estimated the three exogenous shocks and then empirically test the asset pricing implications of the model.

3 Full-Information Bayesian MCMC Estimation

In this section, we develop full-information Bayesian MCMC method for estimating the aforementioned DSGE model based on observed macroeconomic variables. We choose seven macroeconomic variables following **?**: per capita output growth (dy), per capita consumption growth (dc), per capita investment growth (di), wage growth (dw), logarithm of inflation (π), 3-month T-Bill (r), and average weekly hours per capita (h). The three fundamental exogenous shocks are neutral technology shocks $\{\mu_{z,t}\}$, investment-specific technology shocks $\{\mu_{\psi,t}\}$ and monetary policy shocks $\{V_t\}$, defined in equations (5), (6), and (16). Given the initial states, the time-series of the aforementioned three exogenous shocks completely determine the outcome of the economy.

3.1 Solution of the System

Our goal is to solve and estimate the economic system described in Section 2 using the actual economic outcomes observed in history. The model is solved in Dynare [1] to the second order approximation and the details of the solution are provided in the appendix of CTW. Let X_t denote the state variables of the model and classify the variables in X_t into three groups:

- X_t^o: observable endogenous state variables
- X_t^u: unobservable endogenous state variables
- X_t^e: exogenous state variables $= \{\mu_{z,t}, \mu_{\psi,t}, V_t\}$

There are three exogenous shocks $U_t = \{e_t^z, e_t^{\psi}, e_t^V\}$. The variables evolves according the following rules obtained from solving the model

$$\begin{aligned} X_t^o &= \Gamma^o\left(X_{t-1}, U_t^e, \mathbf{\Theta}\right) = \Gamma^o\left(X_{t-1}^o, X_{t-1}^u, X_{t-1}^e, U_t^e, \mathbf{\Theta}\right) \\ X_t^u &= \Gamma^u\left(X_{t-1}^o, X_{t-1}^u, X_{t-1}^e, U_t, \mathbf{\Theta}\right) \\ X_t^e &= \Gamma^e\left(X_{t-1}^o, X_{t-1}^u, X_{t-1}^e, U_t, \mathbf{\Theta}\right) \end{aligned}$$

where Θ is the vector of model parameters

$$\Theta = [\beta, \phi, b, \alpha, \delta, \eta_g, \xi_p, \xi_w, K, \lambda_f, \lambda_w, \sigma_a, \sigma_s, \pi_{ss}, \rho_k, \rho_\pi, \rho_y, m_z, \mu_\psi, \sigma_z, \sigma_\psi, \sigma_v, \rho_z, \rho_\psi, \rho_v]$$

and Γ^e is determined by the following relation:

$$U_t = \begin{bmatrix} e_t^z \\ e_t^\psi \\ e_t^V \end{bmatrix} = \begin{bmatrix} \left[\mu_{z,t} - \mu_z(1-\rho_z) - \rho_z \mu_{z,t-1}\right]/\sigma_z \\ \left[\mu_{\psi,t} - \mu_\psi(1-\rho_\psi) - \rho_\psi \mu_{\psi,t-1}\right]/\sigma_\psi \\ \left[V_t - \rho_v V_{t-1}\right]/\sigma_v \end{bmatrix}.$$

[1]Please find detailed information on Dynare at www.dynare.org.

To calculate X_t, we input the observed values of X^o_{t-1} (denoted as $\tilde{X}^o_{t-1}$) and the model generated values of X^u_t, given the exogenous X^e_t, into the above Γ functions. Therefore, we can calculate X^u_t from the initial values X_0, the time series of $\{\tilde{X}^o_s\}^t_{s=1}$, and the exogenous process $\{U_s\}^t_{s=1}$ as

$$X^u_t = \Gamma^{u,(t)}\left(X_0, \{\tilde{X}^o_s\}^t_{s=1}, \{U_s\}^t_{s=1}, \boldsymbol{\Theta}\right) ,$$

using Γ^u function iteratively for t times. Consequently, the model generated values for observable endogenous variables can be written as

$$X^o_t = \Gamma^o\left(\tilde{X}^o_{t-1}, \Gamma^{u,(t-1)}\left(X_0, \{\tilde{X}^o_s\}^{t-1}_{s=1}, \{U_s\}^{t-1}_{s=1}, \boldsymbol{\Theta}\right), X^e_{t-1}, U^e_t, \boldsymbol{\Theta}\right) .$$

Let Υ_t denote the model solution of the observable variables that we would like to match with the actual observation, which may share some common variables with X_t. Our goal is to choose model parameters Θ and latent variables $\{U_t\}^T_{t=1}$ such that Υ_t is as close to Υ^{obs}_t as possible. Assume that

$$\Upsilon_t = \Gamma\left(X_{t-1}, U_t, \boldsymbol{\Theta}\right) ,$$

where the endogenous variables X_{t-1} is given by

$$X_{t-1} = \left\{\tilde{X}^o_{t-1}, \Gamma^{u,(t-1)}\left(X_0, \{\tilde{X}^o_s\}^{t-1}_{s=1}, \{U_s\}^{t-1}_{s=1}, \boldsymbol{\Theta}\right), X^e_{t-1}\right\} .$$

Based on second order approximation in Dynare, Υ_t depends on the state variables last period (X_{t-1}) and the shocks this period (U_t) to the second order, i.e.,

$$\begin{aligned}
\Upsilon_t &= \Gamma\left(X_{t-1}, U_t, \boldsymbol{\Theta}\right) \\
&= \Upsilon_{\text{steady}}(\Theta) + A + B\, X_{t-1} + C\, U_t + D\, \left(X_{t-1} \otimes X_{t-1}\right) + E\, \left(U_t \otimes U_t\right) + F\, \left(X_{t-1} \otimes U_t\right).
\end{aligned}$$

where $\Upsilon_{\text{steady}}(\Theta)$ represents the steady value of Υ_t and $\otimes$ denotes the Kronecker product. We use matrices

$$\Omega(\Theta) \equiv \begin{bmatrix} \Upsilon_{\text{steady}} & A & B & C & D & E & F \end{bmatrix}$$

to summarize the coefficients in the solution for Υ. We denote the coefficient matrices for the solutions of X_t^u as $\Omega_u(\Theta)$, which are given similarly by

$$\Omega_u(\Theta) \equiv \begin{bmatrix} X^u_{\text{steady}} & A_u & B_u & C_u & D_u & E_u & F_u \end{bmatrix}.$$

All the coefficient matrices depend on model parameters Θ.

3.2 Full-information Bayesian estimation

Define the time series of observable variables as Υ_t^{obs} for $t = 1, \cdots, T$, and assume Υ_t^{obs} are observed with independent pricing errors

$$\Upsilon_t^{obs} = \Upsilon_t + \varepsilon_t = \Gamma(X_{t-1}, \mu_t, \Theta) + \varepsilon_t$$

where $\varepsilon_t = [\varepsilon_{1t}, \cdots, \varepsilon_{7t}], \varepsilon_{it} \sim N(0, \sigma_i^2)$ for $i = 1, \cdots, 7$ and Υ_t is the model implied values from the Γ function that is solved numerically using Dynare package. In the Dynare package, we assume

$$[\Upsilon_t \; X_t^\mu \; X_t^o] = \Gamma(X_{t-1}, \mu_t; \Theta).$$

where the dynamics of μ_t is determined through the following evolution equations

$$\begin{cases} \mu_{z,t} = \mu_z(1-\rho_z) + \rho_z \mu_{z,t-1} + \sigma_z e_t^z \\ \mu_{\psi,t-1} = \mu_\psi(1-\rho_\psi) + \rho_\psi \mu_{\psi,t-1} + \sigma_\psi e_t^\psi \\ V_t = \rho_V V_{t-1} + \sigma_V e_t^V \end{cases},$$

and Θ. Since μ_t $(t = 1, \cdots, T)$ can be uniquely specified by the sequence $(\mu_{z,t}, \mu_{\psi,t}, V_t)$, the main objective of our analysis is to estimate the model parameters, σ_i $(i = 1, \cdots, 7)$ and Θ, and latent state variables $S_t = [\mu_{z,t}, \mu_{\psi,t}, V_t]$ $(t = 1, \cdots, T)$ using observationΥ_t^{obs} $(t = 1, \cdots, T)$. The biggest challenge of the analysis is that the marginal likelihood based on parameters only has to be obtained by integrating out a very high dimensional function (on the order of $3 \times T$ dimension due to latent state variables), creating extremely heavy computing burdens. However, solving for parameters and latent variables seems most feasible using Bayesian MCMC methods. In contrast to classical statistical theory, which uses the likelihood $L(\Theta) \equiv p(\boldsymbol{\Upsilon}|\Theta)$, Bayesian inference adds to the likelihood function the prior distribution for Θ, called $\pi(\Theta)$. The distribution of $(\boldsymbol{\Upsilon}, \mathbf{S})$ and $\pi(\Theta)$ combine to provide a joint distribution for $(\boldsymbol{\Upsilon}, \mathbf{S}, \Theta)$ from which the posterior distribution of $(\Theta, \mathbf{S})$ given $\boldsymbol{\Upsilon}$ is produced

$$p(\Theta, \mathbf{S}|\boldsymbol{\Upsilon}) = \frac{p(\boldsymbol{\Upsilon}, \mathbf{S}, \Theta)}{\int p(\boldsymbol{\Upsilon}, \mathbf{S}, \Theta) d\mathbf{S} d\Theta} \propto p(\boldsymbol{\Upsilon}, \mathbf{S}, \Theta)\,.$$

In our context, it is

$$\begin{aligned}
p(\Theta, \mathbf{S}|\boldsymbol{\Upsilon}) &\propto p(\boldsymbol{\Upsilon}|\mathbf{S}, \Theta) \times p(\mathbf{S}|\Theta) \times \pi(\Theta) \\
&= p(\Upsilon_1^{obs}|\mathbf{S}, \Theta) \times p(\Upsilon_2^{obs}|\Upsilon_1^{obs}, \mathbf{S}, \Theta) \times \cdots \times p(\Upsilon_T^{obs}|[\Upsilon_1^{obs}, \cdots \Upsilon_{T-1}^{obs}], \mathbf{S}, \Theta) \\
&\quad \times p(\mathbf{S}|\Theta) \times \pi(\Theta) \\
&\propto \prod_{t=1}^{T} \prod_{i=1}^{7} \frac{1}{\sigma_i} \exp\{-\frac{1}{2\sigma_i^2}[\Upsilon_t^{obs}(i) - \Upsilon_t(i)]^2\} \\
&\quad \times \prod_{t=1}^{T} \frac{1}{\sigma_z} \exp\{-\frac{1}{2\sigma_z^2}[\mu_{z,t} - \mu_z(1-\rho_z) - \rho_z \mu_{z,t-1}]^2\} \\
&\quad \times \prod_{t=1}^{T} \frac{1}{\sigma_\psi} \exp\{-\frac{1}{2\sigma_\psi^2}[\mu_{\psi,t} - \mu_\psi(1-\rho_\psi) - \rho_\psi \mu_{\psi,t-1}]^2\} \\
&\quad \times \prod_{t=1}^{T} \frac{1}{\sigma_V} \exp\{-\frac{1}{2\sigma_V^2}[V_t - \rho_V V_{t-1}]^2\} \times \pi(\Theta)\,.
\end{aligned}$$

In general, it is difficult to simulate directly from the above high dimensional posterior distribution. The theory underlying the MCMC algorithms that eases the computational burden is the Clifford-Hammersley Theorem. This theorem states that the joint distribution $p(\Theta, \mathbf{S}|\mathbf{\Upsilon})$ can be represented by the complete conditional distributions $p(\Theta|\mathbf{S}, \mathbf{\Upsilon})$ and $p(\mathbf{S}|\Theta, \mathbf{\Upsilon})$. MCMC algorithm is done iteratively. In each iteration, each parameter is updated based on most recent value of all other parameters and latent variables through sampling from the corresponding complete conditional distribution, and the latent variables at each time t is also updated in the similar fashion. As this is done, the chains converge (theoretically), to the target posterior distribution. Therefore, after a sufficient number of samples, called a burn-in period, the algorithm is then sampling from a converged target posterior distribution. To find parameter estimates, however, requires some additional machinery. Use of calculus methods will only work nicely if the prior distributions are conjugate priors, leading to tractable solutions. However, in our analysis here, parameters and latent variables are involved into likelihood through the Dynare package, which is a "black box" for us, resulting in intractable posterior distributions. We therefore turn to Metropolis Hastings Algorithm (MH) for updating both Θ and $\mathbf{S}$. The MH algorithm is an adaptive rejection sampling method where candidate draw is proposed and then accepted with probability proportional to the ratio of the likelihood of the proposed draw to the current draw. This means that if the new position has a higher likelihood (defined using the posterior distribution), then the parameter values are updated with probability 1. Alternatively, if they are less likely, the parameter values are updated with probability according to the likelihood ratio. Thus the parameter values will tend to stay near the highest probability regions when being sampled and adequately cover the probability space. The actual steps involved are as follows provide a vector of starting values for the algorithm, $\Theta^{(0)}$, for iteration g,

- Step 1. Specify a candidate distribution, $h(\Theta|\Theta^{(g-1)})$;

- Step 2. Generate a proposed value for parameters, $\Theta^* \sim h(\Theta|\Theta^{(g-1)})$;

- Step 3. Compute the acceptance ratio

$$\Upsilon_g = \frac{p(\Theta^*) \times h(\Theta^*|\Theta^{(g-1)})}{p(\Theta^{(g-1)}) \times h(\Theta^{(g-1)}|\Theta^*)}$$

where $p(.)$ represents a complete conditional distribution;

- Step 4. Generate $u \sim Unif[0,1]$, then set

$$\Theta^{(g)} = \begin{cases} \Theta^* & if \ \Upsilon_g \geq u \\ \Theta^{(g-1)} & if \ \Upsilon_g < u \end{cases};$$

- Step 5. Set g = g + 1 and return to Step 1.

If the candidate distribution is symmetric, the MH algorithm has acceptance ratio equivalent to $\frac{p(\Theta^*)}{p(\Theta^{(g-1)})}$. In implementation, we chose $h(\Theta|\Theta^{(g-1)}) \sim N(\Theta^{(g-1)}, c^2)$ with some constant variance c^2. The MH algorithm is conducted iteratively on each parameter in Θ and on each latent variable at each time point $t = 1, \cdots, T$. In estimation, we draw posterior samples using the above described MCMC, and use the means of the posterior draws as parameter estimates and the standard deviations of the posterior draws as standard errors of the parameter estimates after a burn-in period. Detailed description about the priors, posterior distributions, and the updating procedures for parameters and latent variables in our model are provided in Appendix A. Table 1 presents the estimated posterior means and standard errors of model parameters, close to what CTW find in their estimation. Figure 1 plots the three exogenous shocks.

4 Cross-Section Tests

In this section, we study the explanatory power of the three latent shocks $\{e_t^z, e_t^\psi, e_t^v\}$ on cross-sectional stock returns. Because our shocks are in quarterly frequency, the estimates of factor loadings are especially noisy. We therefore form mimicking portfolios for the three latent shocks for cross-sectional tests as the literature suggests that the use of factor mimicking portfolios provides sharper estimates of factor loadings. Our choice of testing portfolios are ten equal-weighted size portfolios, ten equal-weighted book-to-market portfolios, and ten equal-weighted asset growth portfolios due to the large return spreads among those portfolios. The size and book-to-market portfolios are taken from Kenneth French's website and the asset growth portfolios are constructed following **?**. Asset growth is defined as year-to-year percentage change in total assets. During the sample period of 1966Q1:2010Q3, the return spreads between the highest and the lowest deciles sorted on size, book-to-market, and asset growth are 2.09%, 3.62% and 3.82% per quarter, respectively.

To form mimicking portfolios of the latent shocks, we follow **?** and **?**. The returns of 30 test assets are first regressed on the three latent shocks to get a (30×3) matrix B of slope coefficients on the three shocks and a covariance matrix V of error terms in the regressions. The mimicking portfolios are then given by $(B'V^{-1}B)B'V^{-1}R'$, where R' is a $T \times 30$ matrix of returns on test portfolios. This procedure gives us the time-series returns on 3 unit-beta mimicking portfolios, defined as factors f_{NT}, f_{IST}, and f_{MP} and each of which has a loading of one on its corresponding latent shock and zero for the other shocks.

Following **?**, we estimate the factor loadings and risk premiums of factors f_{NT}, f_{IST}, and f_{MP} using two-stage cross-section regressions. At the first stage, we estimate factor loadings of the aforementioned three factors for 30 size, book-to-market, and asset growth test portfolios. Given our small number of observations (179 quarters in our sample), we use full-sample estimation of factor loadings. As argued by Liu and Zhang (2008) and shown in **?**, if the true factor loadings are constant, the full-sample estimates should be more precise than estimates based on rolling window and extending window regressions.

Panels A, B, and C of Table 3 present the average quarterly returns and the factor loadings on

f_{NT}, f_{IST}, and f_{MP} for ten size, ten book-to-market, and ten asset growth portfolios, respectively. The row starting with $\bar{r}$ in Panel A shows the average quarterly returns of ten portfolios from lowest market capitalization to the highest. The row starting with NT, IST, and MP shows the slope coefficients of f_{NT}, f_{IST}, and f_{MP}, respectively, in the following regression

$$R_{pt} = \alpha_p + \beta_{NT,p} f_{NT,t} + \beta_{IST,p} f_{IST,t} + \beta_{MP,p} f_{MP,t} + e_{pt} \, ,$$

where R_{pt} is the return on test portfolio p at quarter i. Variables in Panels B and C are similarly defined for ten portfolios ranked by book-to-market ratio and ten portfolios ranked by asset growth rate, respectively. Consistent with Fama and French (1993) and **?**, firms with low market capitalization, high book-to-market ratio, and low asset growth earn higher returns on average in our sample. In terms of the β's, the loadings on factor f_{NT} are statistically indifferent from zero at 5% significance level for all 30 testing portfolios except the one with highest market capitalization. On the opposite, the loadings of factors f_{IST} and f_{MP} are significantly different from zero at 5% level for all 30 testing portfolios except that the loading for f_{IST} is significant at 10% level for the portfolio with highest market capitalization. Figure 5 plots the factor loadings of all 30 test portfolios on factors f_{NT}, f_{IST} and f_{MP}.

Table 3 and Figure 5 show that firms with smaller size, higher book-to-market ratio, and higher asset growth rate tend to have larger exposure to f_{IST}. In the model, a positive IST shocks indicate cheaper capital goods relative to consumption goods. Empirical estimate of IST shock (see Cummins and Violante (2002) among others) computes the quality-adjusted prices of equipment and software (E&S) including industrial equipment, transportation equipment, information processing equipment and software, and other equipment as price of capital goods. Intuitively, firms that employ new technology, capital intensive production technology, or undergoes capital investments will have larger exposures to the IST factor f_{IST}. Our results are consistent with the convention that smaller firms are more likely to be startup firms in high-tech industries, value firms are usually capital intensive, and high asset growth firms invest more.

Firms with smaller size and lower asset growth rate have larger exposure to f_{MP}, although the relations are not monotonic and instead hump-shaped. The spread in risk exposure to f_{MP} among book-to-market portfolios is small. The two extreme portfolios have similar factor loadings and the intermediate ones have lower loadings. Because monetary policy shocks affect the credit tightness, the results suggest that smaller firms, firms with lower growth rate, and firms with extreme book-to-market ratios are more sensitive to the credit condition of the financial market.

The factor loadings on f_{NT} are mostly not significantly different from zero for our test assets. Nevertheless, our estimates show that firms with larger size, higher book-to-market ratio, or lower asset growth rate have large exposure to f_{NT}. Neutral technology shock refers to productivity changes that are not specific to capital goods and affect the productivities of both capital and labor equally. Therefore, neutral technology shocks mostly reflect "general-purpose' technological changes that affect all firms similarly and may not generate significant return spreads cross-sectionally.

In general, the evidence from slope coefficients from time-series regressions suggests that factors f_{IST} and f_{MP} but not f_{NT} have explanatory powers on cross-sectional stock returns. Once obtaining the factor loadings in the first step, we preform second-step cross-sectional regressions of portfolio excess returns on these factor loadings at each quarter. The estimated risk premiums for the three factors are the time-series average regression coefficients on their corresponding factor loadings and t-statistics are Shanken (1992) corrected.

Panel A of Table 4 presents the estimated risk premiums for factors f_{NT}, f_{IST}, and f_{MP}. It shows that the risk premiums for f_{IST} and f_{MP} are statistically different from zero at 1% significance level and the risk premium of f_{NT} is only significant at 10%. The results echo the conclusion based on factor loadings in the first stage, where only 1 out of 30 test portfolios loads significantly on f_{NT}. The signs of the risk premiums, positive for f_{NT} and f_{IST} and negative for

f_{MP}, are consistent with the model predictions in Section 2.5. The magnitude of risk premium for f_{IST} is largest (1.35% per quarter), followed by f_{MP} (−0.35%) and f_{NT} (0.12%). The adjusted R^2 is 49% and the α is 0.77% per quarter with t-statistic 1.04, which suggests that our three factors explain a large portion of the cross-sectional average return variation among the 30 test portfolios and the unpriced return α is not significant.

Panels B, C, and D present the fractions of average return differences explained by factors of f_{NT}, f_{IST}, and f_{MP} for two extreme size, book-to-market, and asset growth portfolios, respectively. Panel B shows that the average returns of smallest and largest size portfolio are 3.26% and 1.17% per quarter, generating 2.09% average return difference. Define expect return of portfolio p as the product of estimated factor risk premium in Panel A of Table 4 and the corresponding factor landings for portfolio p in Table 3, i.e.,

$$\mathrm{E}[r_p] = \hat{\beta}_{NT}\hat{\gamma}_{NT} + \hat{\beta}_{IST}\hat{\gamma}_{IST} + \hat{\beta}_{MP}\hat{\gamma}_{MP} \, ,$$

where $\hat{\beta}_X$ is estimated factor loading for X and $\hat{\gamma}$ is its risk premium. To understand the how much return difference between extreme portfolios can be explained by our risk factors, we compute the ratio of expected to observed average return difference, denoted by

$$\ell = \frac{E(\bar{r}_L) - E(\bar{r}_H)}{\bar{r}_L - \bar{r}_H} \, ,$$

where r_H and r_L are the returns of extreme portfolios. We also compute the same ratio for expected return contributed by each specific risk factor. Panel B shows that our risk factors over-explain the average return difference between smallest and largest size portfolios, with ℓ being 140%. Among the three factors, f_{IST} contributes most, with $\ell_{IST} = 268\%$, followed by f_{MP} ($\ell_{MP} = -123\%$) and f_{NT} ($\ell_{MP} = -5\%$) in decreasing order.

Panel C shows that the average return difference between lowest to highest book-to-market portfolios is -3.62% per quarter, 60% being explained by the three risk factors. Similarly, f_{IST} contributes most, explaining 60% of average return difference. The contributions of f_{MP} and f_{NT} are opposite in signs, being 6% and -6% respectively, and cancels out each other. The return difference between lowest and highest asset growth portfolios, presented in Panel D, is -3.82% per quarter, 55% of which being explained by the three risk factors. Again, f_{IST} alone contributes 74% to the return difference, -22% by f_{MP} and 3% by f_{NT}.

Overall, the above results indicate that our risk factors f_{IST}, f_{NT} and f_{MP} explain well the cross-sectional return differences among 30 size, book-to-market, and asset growth portfolios. Both factor loadings and risk premiums for f_{IST} and f_{MP} are significantly different from zero. Factor f_{IST} has a much larger risk premium than f_{MP} and contributes most to the return differences between extreme portfolios. Even though the sign of risk premium for f_{NT} is consistent with what the model predicts, neither its factor loadings nor risk premium are statistically significant. One possible explanation is that neutral technology shock reflects "general-purpose" technological changes that affect firms equally and does not generate substantial return spread cross-sectionally, which leads to inaccurate estimation of its factor loadings and risk premium.

5 Predictive Tests

In this section, we explore the predictive power of the three latent variables $\{\mu_t^z, \mu_t^\psi, V_t\}$ on aggregate stock market returns, long-term corporate bond returns, and long-term government bond returns at one-month, one-quarter, and one-year horizon, respectively. Moreover, we compare the performance of our latent variables with a set of macroeconomic that have been shown to have predictive powers on stock/bond returns in the literature, including the *cay* factor in Lettau and Ludvigson (2001) and the *gap* factor in Cooper and Priestley (2009). Our latent shocks are estimated using the seven macroeconomic variables for sample period 1966Q1 to 2010Q3 because of the poor quality of macro data before 1966Q1 (**?**). All macroeconomic data is from the DRI data set from WRDS. Market stock returns are proxied by CRSP value-weighted return, taken from Ken French's website. Long-term corporate and government bond returns are from Ibbotson Associates.

The *cay* factor is constructed for period of 1966Q1-2010Q3 based on

$$cay_t = c_{n,t} - \hat{\beta}_1^c a_t - \hat{\beta}_2^c l_t ,$$

where $c_{n,t}$ is log of nondurable consumption, a_t is log of asset holdings, l_t is log of labor income. [2] The coefficients in the above equation comes from the following regression

$$c_{n,t} = a^c + \beta_1^c a_t + \beta_2^c l_t + \sum_{i=-8}^{8} \beta_{1,i}^c \Delta a_{t-i} + \sum_{i=-8}^{8} \beta_{2,i}^c \Delta l_{t-i} .$$

Lettau and Ludvigson (2001) show that the *cay* factor is a good proxy for market expectations for future returns under certain conditions.

The *gap* factor is constructed for period of 1966Q1-2010Q3 based on quarterly industry production index (IP), which is also from the DRI data set, according to following regression model

$$IP_t = a + \beta_1^g t + \beta_2^g t^2 + gap_t$$

for the aforementioned sample period. [3] Cooper and Priestley (2009) do not provide a theory behind the *gap* factor but show that *gap* has an excellent predictive power of future returns empirically.

[2]Data on consumption, asset holdings, and labor income are from Sydney Ludvigson's website.
[3]Please see Cooper and Priestley (2009) for details.

5.1 Summary statistics

Panel A of Table 2 presents the correlations between the macroeconomic variables used in our estimation and the three estimated latent variables and the correlations between the latent variables and the *cay* factor and the *gap* factor. There are three main observations: (1) Both neutral technology shocks NT and investment-specific technology shock IST are positively correlated with output growth, consumption growth, and investment growth but negatively correlated with inflation. This result is consistent with our intuition and what CTW find because higher productivity leads to higher contemporaneous output, consumption, and investment. (2) NT is positively correlated with wage while the correlation between NT and wage is close to zero and negative. Neutral technology shock improves the productivity of labor hence the wage rate. investment-specific technology shocks also improves the productivity of labor due to high capital level, but can decrease the demand for labor and generates a downward pressure on wage rate. The final effect depends on which of the aforementioned two effects dominates. (3) Both neutral technology shock and investment-specific technology shock have a positive (although small) correlation with interest rate. Higher productivity leads to higher output, which through Taylor rule results in a higher interest rate.

The *cay* factor is highly correlated with the investment-specific technology shock and modestly correlated with monetary policy shock. The correlation coefficients are 0.64 and 0.15, respectively. The correlation between *cay* and the neutral technology shock is -0.02 and close to zero. The *gap* factor is positively correlated monetary policy shock and negatively correlated with the two technology shocks, although the magnitudes of the correlation coefficients are all small, being -0.05, -0.11, and 0.08, respectively. Panel C reports the results from contemporaneous regressions of cay/gap on the latent variables. Consistently with the correlation matrix shows, our estimated latent variables explain around 41% of the movement in *cay* with the loading on IST being statistically significant (*t-stat* = 10.68). Contrarily, the latent variables only explain 3.81% of the movements in *gap* even though the loadings on IST and MP are statistically significant (*t-stat* $= -2.13$ and *t-stat* $= 2.14$, respectively) . This result shows that *gap* captures some other fundamental shocks that are not in our model. Industry Production Index measures real production output of specific industries including manufacturing, mining, and utilities while our model treats the whole economy as one sector. Our guess is that the *gap* factor may contain specific information on the aforementioned three industries that is not captured by our seven aggregate macroeconomic variables.

5.2 Predictive Regressions

To explore the predictive power of the latent variables, we follow Lettau and Ludvigson (2001) and Cooper and Priestley (2009) and use the following predictive regression

$$R_{t+\tilde{1}} = \alpha + \beta\, X_t + \epsilon_t\,, \tag{19}$$

where α is the regression intercept, β is the coefficient vector, and X_t is the vector of explanatory variables of quarter t. Here, $R_{t+\tilde{1}}$ is the excess returns on certain asset of the subsequent month, quarter, or year of quarter t for predictive regression at one-month horizon, one-quarter horizon, or one-year horizon, respectively. Therefore, $\tilde{1}$ refers to one month, one quarter, or one year accordingly. We test the predictive power of the latent variables, i..e, $X_t = [\mu_t^z,\, \mu_t^\psi,\, V_t]$, on excess returns of three asset classes: aggregate stock market, long-term corporate bond, and long-term government bond. For comparison reason, we also report the predictive power of other popular predictors of stock or bond returns such as cay, gap, d/p, e/p, dfy, and tms. Because our latent variables are constructed from macroeconomic variables, we focus on the comparison with other macroeconomic predictors cay and gap.

5.2.1 Stock Return Prediction

Table 5 reports the regression coefficients using the latent variables as independent variables at three horizons, one-month, one-quarter, and one-year horizon. Panel A presents the results for the full sample period: 1966Q1 - 2010Q3. Panels B and C presents the results for two subsamples: 1970Q1-2010Q3 and 1975Q1 and 2010Q3. The choices of subsamples are chosen based on the observation in Welch and Goyal (2009) that most of successful predictors for stock returns are found to perform much worse in these two subsamples. The reported t-statistics are corrected for heteroskedasticity and serial correlation, up to two lags, using the Newey and West (1987) estimator.

The main observation from Table 5 is that our estimated latent shocks preforms well in all three sample periods with the adjusted R-squares ranging from 1.55% to 3.08% for one-month horizon, from 2.07% to 4.27% for one-quarter horizon, and from 7.39% to 12.62% for one-year horizon. The sample period 1975Q1-2010Q3 perform the worst. Most of the predictive power comes from the neutral technology shocks and the monetary policy shocks. The regression coefficients of NT and MP are almost all significant at 5% level. The explanatory power of the investment-specific technology shock is weak at one-month horizon, gets stronger at one-quarter horizon and becomes significant at 5% level at one-year horizon. This observation is present in all there sample periods. Consistent at all horizons and all sample periods, a positive neutral technology shock and a higher investment-specific technology shock lead to higher future stock returns, while higher monetary policy shocks leads to lower future stock returns. It is intuitive that higher technology level leads to higher profitability hence higher returns. The negative relation between monetary policy shocks and stock returns are consistent with the findings in Bernanke and Kuttner (2005) and may be explained by the higher financing cost of firms after a positive monetary policy shock.

We also compare the predictability of our estimated latent shocks with two of the most successful stock return predictors in the literature, the *cay* factor and the *gap* factor. Besides the success of *cay* and *gap* in predicting returns, we choose those two factors because they are constructed based on macroeconomic variables in stead of prices, such as dividend-to-price ratio. Table 6 reports the regression coefficients, the corresponding Newey-West t-statistics, and the adjusted R-squares of the estimated latent shocks, the *cay* factor, and the *gap* factor at one-month horizon. For all three sample periods, both *cay* and *gap* have a (adjusted) R-square of zero and either the coefficients of *cay* or those of *gap* are significant at 5% level. Latent variable MP has the best explanatory power among the three latent variables, whose regression coefficient is significant at 5% level for all three periods. The coefficient of NT is significant at 5% level for period 1975Q1-2010Q3 and only significant at 10% level for periods 1966Q1 - 2010Q3 and 1070Q1 - 2010Q3. The coefficient of IST is not significant for all three periods. The period of 1975Q1 - 2010Q3 is the most unpredictable period for all the predictors at one-month horizon.

Table 7 compares the predictability of the latent shocks, the *cay* factor, and the *gap* factor at one-quarter horizon. The latent shocks still have the best predictive power at one-quarter horizon. The R-squares of *cay* and *gap* are lower than those of the latent shocks for all three sample periods. The coefficients of *cay* and *gap* are significant at 5% level for all three periods. Moreover, higher *cay* predicts higher future stock returns while higher *gap* predicts lower future returns. The coefficient of IST remains insignificant. The coefficients of NT and MP are significant at 5% level for all periods except that the coefficient of MP is not significant for period 1975Q1 - 2010Q3. For all predictors, period 1975Q1 - 2010Q3 remains to be the most unpredictable period.

Table 8 compares the predictability of the latent shocks, the *cay* factor, and the *gap* factor at one-year horizon. Similar to the observation at one-month and one-quarter horizons, our estimated latent variables have a better predictability than *cay* and *gap*. The coefficients of *cay* and *gap* are significant at 5% level, indicating some predictive power. The coefficients of NT, IST, and MP are significant at 5% level except the coefficient of NT for period 1966Q1 - 2010Q3.

In summary, our estimated latent shocks has a predictive power on aggregate stock returns that is to the least not worse than *cay* and *gap*. Mover, consistent with the model predictions in Section 2.5, positive neutral and investment-specific technological shocks and negative monetary policy shocks predict higher future stock returns. The relation between the three shocks and future returns are economically intuitive. Higher neutral technology shocks and higher investment-specific technology shocks means higher profits in the future hence higher return. Higher monetary policy shocks predict lower future returns due to higher financing costs for firms. Consistent with the positive and high correlation between *cay* and NT shown in Table 2, the *cay* factor has a similar relation with stock returns as NT. However, the economic intuition behind *gap* is hard to interpret. *gap* has very low correlation with any of the three latent shocks and higher *gap* predicts lower future returns.

5.2.2 Long-Term Corporate and Government Bond Returns

In this section, we conduct the same tests on excess returns on long-term corporate and government bond returns and compare the performance of the latent variables with *cay* and *gap*. Table 9 reports the results from regression (19) of long-term corporate bond returns on the latent variables for all three data periods. For the full sample period 1966Q1-2010Q3, the adjusted R-squares are 6.83%, 5.93%, and 8.84% at one-month, one-quarter, and one-year horizon, respectively as shown in Panel A. The loadings of IST and MP are significant at 5% level for all three horizons except for one-quarter horizon in which case the loading on IST is significant at 10%. The loading of NT is significant at 5% level only for one-month horizon and loses its significance at longer horizons. In general, corporate bond returns are explained mostly by IST and MP, compared to stock returns explained mostly by NT and MP. Same observations are found for the two subsample periods. The predictive power is worst for period 1975Q1-2010Q3, similar with the findings on stock returns.

Tables 10, 11 and 12 compare the predictive power of the latent variables with *cay* and *gap* on long-term corporate bond returns at one-month, one-quarter, and one-year horizons, respectively.

A one month horizon, the latent variables have significantly larger predictive power than *cay* and *gap*. For the full sample period 1966Q1-2010Q3, the adjusted R-square of the latent variables is 6.84%, compared to 0.79% and 0.48% for *cay* and *gap* respectively. The loading of NT is significant at 5% level and the loadings of IST and MP are significant at 2% level. Similar observations are found for the two subperiods. At one-quarter horizon, the R-square of *gap* rises to 3.05% however is still lower than that of the latent variables, which is 5.90%. The predictive power of *cay* on corporate bond returns remains low at one-quarter horizon (R-square=0.14%). At one-year horizon, the predictive power of *gap* (R-square = 9.36%) surpasses that of the latent variables (R-square = 8.84%) although the difference is small. The predictive power of *cay* remains the lowest among the three (R-square = 2.05%).

Table 13 reports the results from regression (19) of long-term government bond returns on the latent variables for all three data periods. The adjusted R-squares, 3.22%, 2.55%, and 3.33% at one-month, one-quarter, and one-year horizons respectively for the full sample, are generally lower than those in regressions of long-term corporate bond returns. Latent variable NT has explanatory power only at one-month horizon, whose loading is significant at 10%. Opposite with NT, MP has explanatory power on government bond returns only at one-quarter and one-year horizons with a loading of 5% significance. The loading of IST is significant at 5% level at one-month horizon and at 10% level at one-year horizon, but loses its explanatory power at one-quarter horizon. The same observations hold for the two subperiods.

Tables 14, 15 and 16 compare the predictive power of the latent variables with *cay* and *gap* on long-term government bond returns at one-month, one-quarter, and one-year horizons, respectively. The latent variables perform better than *cay* and *gap* consistently for all three sample periods and at all predictive horizons even though they all lose predictive power for the subperiod 1975Q1-2010Q3 at one-year horizon, in which case no loadings are significant and R-squares are all below 1%.

To summarize, the latent variables have superior predictive powers on long-term corporate and government bonds returns over *cay* and *gap* in most of the cases except that *gap* outperforms the latent variables in predicting long-term corporate bond returns at one-year horizon by a small margin. All the variables predict corporate bond returns better than government bond returns. And once again, positive neutral and investment-specific technological shocks and negative monetary policy shocks predict higher future bond returns, consistent with the model predictions in Section 2.5,

5.3 Robustness Check

As a robustness check, we compare the predictive power of the latent variables on aggregate stock market returns and long-term corporate and bond returns with that of a set of financial variables, including *dividend price ratio* (d/p), *earnings price ratio* (e/p), *default yield spread* (dfy), *term spread* (tms). Among these financial variables, d/p and e/p are variables constructed from aggregate stock market while dfy and tms are from corporate and government bond markets. The *dividend price ratio* (d/p) is the difference between the log of 12-month moving sums of dividends paid on the S&P 500 index and the log of the S&P 500 index prices. The *earnings price ratio* (d/p) is the difference between the log of 12-month moving sums of earnings paid on the S&P 500 index and the log of the S&P 500 index prices. The *default yield spread* is the difference between BAA and AAA-rated corporate bond yields. The *term spread* is the difference between the long-term yield on government bonds and the 3-month Treasury Bill. All financial data is from Amit Goyal's website.

Tables 17, 18, and 19 report the results from predictive regressions of stock market returns and long-term corporate and government bond returns, respectively, on the latent variables, d/p, e/p, dfy, and tms for the full sample period 1966Q1-2010Q3 [4] at all three horizons. Overall, the predictive power of the latent variables beats that of d/p, e/p and dfy across all three asset classes

[4]Results for the two subperiods are qualitatively similar.

at all horizons. Term premium *tms* has a weaker predictive power on stock market returns than the latent variables but has a stronger predictive power on long-term corporate and government bond returns.

6 Conclusion

A full-information Bayesian Markov Chain Monte Carlo (BMCMC) method is developed for estimating DSGE models using macroeconomic variables. We implement this method on a standard medium-size DSGE model based on CTW and extract three exogenous latent shocks: neutral technology shock, investment-specific technology shock, and monetary policy shock. The estimated latent shocks are shown to explain well cross-sectional return differences among 20 size, book-to-market, and asset growth test portfolios and exhibit excellent predictive power for future aggregate stocks returns at one-month, one-quarter, and one-year horizon for all three sample periods examined in the study: 1966Q1-2010Q3, 1970Q1-2010Q3, and 1975Q1-2010Q3. Compared with *cay* and *gap*, our estimated latent shocks have greater and more robust predictive power.

A Posteriors

In this appendix, we provides a brief description about the priors, posterior distributions, and the updating procedures for parameters and latent variables in our model.

- *Posterior of* $\sigma_i (i = 1, \cdots, 7)$ — Set the prior of σ_i as $\sigma_i^2 \sim IG(a, b)$, where a,b are hyper-parameters. The posterior of σ_i^2 is

$$\sigma_i^2 \sim IG(\frac{T}{2} + a, A)$$

where

$$A = \sum_{t=1}^{T} \frac{1}{2} (\Upsilon_t^{obs}(i) - \Upsilon_t(i))^2 + b\,.$$

- *Posterior of* $\Theta_i (i = 1, \cdots, 25)$ — Set the prior of Θ_i as ${\Theta_i}^2 \sim N(m, M^2)$ where m, M are hyper-parameters. The posterior of Θ_i is

$$\begin{aligned} p\left(\Theta_i | \Theta_{[-i]}, \mathbf{S}, \boldsymbol{\Upsilon}\right) \quad \propto \quad & \prod_{t=1}^{T} \prod_{i=1}^{7} \frac{1}{\sigma_i} \exp\{-\frac{1}{2\sigma_i^2} [\Upsilon_t^{obs}(i) - \Upsilon_t(i)]^2\} \\ & \times \prod_{t=1}^{T} \frac{1}{\sigma_z} \exp\{-\frac{1}{2\sigma_z^2} [\mu_{z,t} - \mu_z(1 - \rho_z) - \rho_z \mu_{z,t-1}]^2\} \\ & \times \prod_{t=1}^{T} \frac{1}{\sigma_\psi} \exp\{-\frac{1}{2\sigma_\psi^2} [\mu_{\psi,t} - \mu_\psi(1 - \rho_\psi) - \rho_\psi \mu_{\psi,t-1}]^2\} \\ & \times \prod_{t=1}^{T} \frac{1}{\sigma_V} \exp\{-\frac{1}{2\sigma_V^2} [V_t - \rho_V V_{t-1}]^2\} \times \pi(\Theta) \times \exp\{-\frac{(\Theta_i - m)^2}{2M^2}\}\,, \end{aligned}$$

where $\Theta_{[-i]}$ contains the most recent values of other parameters in Θ. In implementation, we simplify the above posterior through abandoning terms that do not depend on Θ_i, and use MH algorithm to update Θ_i.

- *Posterior of* $\{\mu_{z,t}, \mu_{\psi,t}, V_t\}$ $(t = 1, \cdots, T)$ — The posterior distribution of $\mu_{z,t}$ $(for\ 1 \leq t <$

T) is

$$
\begin{aligned}
& p\left(\mu_{z,t} | \Theta, \{\mu_{z,1}, \cdots, \mu_{z,t-1}, \mu_{z,t+1}, \cdots, \mu_{z,T}\}, \{\mu_{\psi,t}\}_{t=1}^{T}, \{V_t\}_{t=1}^{T}, \boldsymbol{\Upsilon}\right) \\
\propto \ & \prod_{s=t}^{T} \prod_{i=1}^{N} \exp\{-\frac{1}{2\sigma_i^2}[\Upsilon_t^{obs}(i) - \Upsilon_t(i)]^2\} \\
& \times \exp\{-\frac{1}{2\sigma_z^2}[\mu_{z,t} - \mu_z(1-\rho_z) - \rho_z \mu_{z,t-1}]^2\} \\
& \times \exp\{-\frac{1}{2\sigma_z^2}[\mu_{z,t+1} - \mu_z(1-\rho_z) - \rho_z \mu_{z,t}]^2\} \, .
\end{aligned}
$$

For $t = T$, the posterior distribution only involves the first two terms in the above equation. Again, MH algorithm is used to update $\mu_{z,t}$. Updating of $\mu_{\psi,t}$ and V_t ($t = 1, \cdots, T$) are done in the same way. The analogous posterior distribution for $\mu_{\psi,t}$ is,

$$
\begin{aligned}
& p\left(\mu_{\psi,t} | \Theta, \{\mu_{\psi,1}, \cdots, \mu_{\psi,t-1}, \mu_{\psi,t+1}, \cdots, \mu_{\psi,T}\}, \{\mu_{z,t}\}_{t=1}^{T}, \{V_t\}_{t=1}^{T}, \boldsymbol{\Upsilon}\right) \\
\propto \ & \prod_{s=t}^{T} \prod_{i=1}^{N} \exp\{-\frac{1}{2\sigma_i^2}[\Upsilon_t^{obs}(i) - \Upsilon_t(i)]^2\} \\
& \times \exp\{-\frac{1}{2\sigma_\psi^2}[\mu_{\psi,t} - \mu_\psi(1-\rho_\psi) - \rho_\psi \mu_{\psi,t-1}]^2\} \\
& \times \exp\{-\frac{1}{2\sigma_\psi^2}[\mu_{\psi,t+1} - \mu_\psi(1-\rho_\psi) - \rho_\psi \mu_{\psi,t}]^2\} \, .
\end{aligned}
$$

The analogous posterior distribution for V_t is,

$$
\begin{aligned}
& p\left(V_t | \Theta, \{V_1, \cdots, V_{t-1}, V_{t+1}, \cdots, V_T\}, \{\mu_{z,t}\}_{t=1}^{T}, \{\mu_{\psi,t}\}_{t=1}^{T}, \boldsymbol{\Upsilon}\right) \\
\propto \ & \prod_{s=t}^{T} \prod_{i=1}^{N} \exp\{-\frac{1}{2\sigma_i^2}[\Upsilon_t^{obs}(i) - \Upsilon_t(i)]^2\} \\
& \times \exp\{-\frac{1}{2\sigma_V^2}[V_t - \rho_V V_{t-1}]^2\} \\
& \times \exp\{-\frac{1}{2\sigma_V^2}[V_{t+1} - \rho_V V_t]^2\} \, .
\end{aligned}
$$

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Table 1: **Estimated Parameters and Estimation Errors**

Panel A of this table reports the parameters values estimated using the Bayesian Markov Chain Monte Carlo method based on 50,000 Monte Carlo iterations. Observed macroeconomic variables used in the estimation are output growth (dy), consumption growth(dc), investment growth (di), wage growth (dw), logarithm of inflation (π), 3-month T-Bill (r), and employment (h). Sample period is 1966Q1 - 2010Q3. Panel B of this table reports the estimation errors of the seven observed macroeconomic variables.

Parameter	Posterior Mean	Posterior Standard Error
Panel A: Estimated parameter values		
β	0.9980	0.0005
ϕ	1.3838	0.0366
b	0.9598	0.0111
α	0.2308	0.0006
ξ_p	0.6022	0.0064
ξ_w	0.8232	0.0029
λ_f	1.1640	0.0024
λ_w	1.0373	0.0008
σ_a	0.2463	0.0242
σ_s	4.6910	0.2075
π_{ss}	1.0071	0.0023
ρ_R	0.7947	0.0036
ρ_π	1.6597	0.0524
ρ_y	0.1505	0.0079
μ_z	0.0038	0.0001
μ_ψ	0.0025	0.0003
ρ_z	0.1207	0.0664
ρ_ψ	0.7455	0.0500
ρ_v	0.3101	0.0534
σ_z	0.0026	0.0004
σ_ψ	0.0029	0.0003
σ_v	0.0021	0.0001
Panel B: Estimation errors		
σ_{dy}	0.8277	0.0446
σ_{dc}	0.4954	0.0268
σ_{di}	3.2050	0.1695
σ_{dw}	0.6202	0.0341
σ_π	0.1702	0.0161
σ_r	0.0817	0.0115
σ_h	2.9769	0.1874

Table 2: **Summary Statistics**

Panel A of this table presents the correlations between macroeconomic variables, including per capita output growth (dy), per capita consumption growth(dc), per capita investment growth (di), wage growth (dw), logarithm of inflation (π), 3-month T-Bill (r), and average weekly hours per capita(h), and estimated latent variables, including the neutral technology shock (NT), investment-specific technology shock (IST), monetary policy shock (MP), and the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is taken from Sidney Ludvigson's website. The output *gap* factor is the residual μ_t from the following regression over the 1966Q01 and 2010Q03 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at quarter t. Panels B of this table reports the correlation matrix between latent variables. All data are sampled quarterly from 1966Q1 to 2010Q3.

	Panel A: Correlations between macro and latent variables			
	NT	IST	MP	
dy	0.31	0.25	0.38	
dc	0.21	0.21	0.31	
di	0.25	0.18	0.30	
dw	0.21	-0.03	0.03	
pi	-0.31	-0.32	-0.06	
r	0.04	0.04	0.48	
h	0.03	0.37	0.24	
cay	-0.02	0.64	0.15	
gap	-0.05	-0.11	0.08	
	Panel B: Correlations between latent variables			
NT	1.00			
IST	0.07	1.00		
MP	0.37	0.39	1.00	
	Panel C: Regression of *cay* and *gap* on latent variables			
				$\bar{R}^2(\%)$
cay	-0.36	2.21	-0.56	41.18
	(-0.65)	(10.68)	(-1.10)	
gap	-2.94	-1.84	4.68	3.81
	(-1.28)	(-2.13)	(2.14)	

Table 3: **Risk Exposures to NT, IST, and MP Shocks for Portfolios Formed on Size, Book-to-market Ratio, and Asset Growth**

Panels A, B, and C of this table reports the average quarterly returns and their risk exposures to estimated latent shocks for ten equal-weighted size portfolios, ten equal-weighted book-to-market portfolios, and ten equal-weighted asset growth portfolios, respectively. The risk exposures are measured as slope coefficients βs in the following regression: $R_{it} = \alpha_i + \beta_i^{NT} f_{NT,t} + \beta_i^{IST} f_{IST,t} + \beta_i^{MP} f_{MP,t} + e_{it}$, where R_{it} is the returns of test portfolio i at quarter t and f_{NT}, f_{IST}, and f_{MP} are returns on mimicking portfolios of shocks NT, IST, and MP, constructed following **?** and **?**. Size and book-to-market portfolios are taken from Kenneth French's website. Asset growth portfolios are constructed following **?**. $\bar{r}$ denotes average portfolio returns. The sample is 1966Q1:2010Q3. The t-statistics are in parentheses and Newey-West corrected. Returns are in quarterly frequency and in percentage.

Decile	Low	2	3	4	5	6	7	8	9	High
					Panel A: Equal-weighted size portfolios					
$\bar{r}$	3.26	2.04	2.18	2.03	2.08	1.91	1.97	1.72	1.58	1.17
NT	2.21	1.31	1.79	1.51	0.95	1.27	0.79	0.88	1.94	3.08
	(0.86)	(0.55)	(0.80)	(0.71)	(0.45)	(0.67)	(0.42)	(0.49)	(1.23)	(2.43)
IST	5.73	3.96	3.72	3.38	2.86	2.31	2.65	2.10	2.25	1.58
	(6.60)	(4.18)	(3.81)	(3.52)	(2.79)	(2.41)	(2.77)	(2.23)	(2.48)	(1.92)
MP	14.44	10.76	9.22	8.59	8.37	7.13	7.20	5.64	5.60	7.16
	(5.84)	(4.44)	(4.03)	(4.15)	(4.00)	(3.79)	(3.71)	(3.00)	(3.53)	(4.89)
					Panel B: Equal-weighted book-to-market portfolios					
$\bar{r}$	0.88	1.82	2.08	2.80	2.59	2.87	3.07	3.20	3.74	4.50
NT	1.63	-0.06	0.49	-0.33	0.85	1.44	1.63	0.61	2.10	3.34
	(0.62)	(-0.03)	(0.23)	(-0.13)	(0.41)	(0.72)	(0.87)	(0.31)	(1.00)	(1.25)
IST	3.96	4.18	3.72	4.42	3.61	3.90	3.91	4.22	4.59	5.57
	(2.97)	(3.88)	(4.29)	(4.28)	(4.58)	(4.95)	(5.44)	(5.41)	(5.58)	(5.49)
MP	12.20	11.57	11.06	11.39	10.49	10.13	9.72	9.54	9.97	12.76
	(4.97)	(5.23)	(5.25)	(5.53)	(5.31)	(5.15)	(5.03)	(4.48)	(4.23)	(4.52)
					Panel C: Equal-weighted asset growth portfolios					
$\bar{r}$	4.83	3.75	3.45	3.12	3.03	2.78	2.78	2.58	2.00	1.01
NT	2.36	2.35	1.90	0.86	1.19	1.75	1.26	0.41	0.90	1.56
	(0.75)	(0.99)	(0.89)	(0.43)	(0.58)	(0.89)	(0.63)	(0.19)	(0.38)	(0.59)
IST	6.21	4.70	4.55	4.33	3.81	4.27	3.93	3.60	3.59	4.11
	(5.59)	(5.44)	(5.70)	(5.67)	(4.83)	(6.15)	(4.82)	(4.30)	(3.83)	(3.40)
MP	15.60	10.81	10.27	10.14	10.19	9.47	10.23	10.28	11.84	13.23
	(5.59)	(4.76)	(5.14)	(5.38)	(5.26)	(4.89)	(4.91)	(4.63)	(5.06)	(5.01)

Table 4: **Risk Premiums of Fundamental Shocks**

Panel A reports the estimated risk premium of factors f_{NT}, f_{IST}, and f_{MP} following **?** and using factor loadings reported in Table 3. Panels B and C report the average returns and their exposures to factors f_{NT}, f_{IST}, and f_{MP} of extreme portfolios sorted on size, book-to-market ratio, and asset growth rate, respectively. Define the fraction of average return difference between extreme portfolios explained by factor X as $\ell_X = \frac{E(\bar{r}_L)-E(\bar{r}_H)}{\bar{r}_L-\bar{r}_H}$, where E($\bar{r}$) is the expected return based on estimated factor loadings and risk premiums. ℓ_{all} denotes the fraction of average return difference explained by all three factors. Size and book-to-market portfolios are taken from Kenneth French's website. Asset growth portfolios are constructed following **?**. $\bar{r}$ denotes average portfolio returns. The sample is 1966Q1:2010Q3. The t-statistics are in parentheses and Newey-West corrected. Returns are in quarterly frequency and in percentage.

Panel A: Risk premium

α	NT	IST	MP	$\bar{R}^2$
0.77	0.12	1.35	-0.35	0.49
(1.04)	(1.67)	(6.53)	(-3.91)	

Panel B: Equal-weighted size portfolios

$Size$	NT	IST	MP	$\bar{r}$	ℓ_{NT}	ℓ_{IST}	ℓ_{MP}	ℓ_{all}
Low	2.21	5.73	14.44	3.26				
	(0.86)	(6.60)	(5.84)					
High	3.08	1.58	7.16	1.17	-0.05	2.68	-1.23	1.40
	(2.43)	(1.92)	(4.89)					

Panel C: Equal-weighted book-to-market portfolios

B/M	NT	IST	MP	$\bar{r}$	ℓ_{NT}	ℓ_{IST}	ℓ_{MP}	ℓ_{all}
Low	1.63	3.96	12.20	0.88				
	(0.62)	(2.97)	(4.97)					
High	3.34	5.57	12.76	4.50	0.06	0.60	-0.06	0.60
	(1.25)	(5.49)	(4.52)					

Panel D: Equal-weighted asset growth portfolios

AG	NT	IST	MP	$\bar{r}$	ℓ_{NT}	ℓ_{IST}	ℓ_{MP}	ℓ_{all}
Low	2.36	6.21	15.60	4.83				
	(0.75)	(5.59)	(5.59)					
High	1.56	4.11	13.23	1.01	0.03	0.74	-0.22	0.55
	(0.59)	(3.40)	(5.01)					

Table 5: **Return Predictability of Estimated Latent Variables: Stock Market Returns**

This table reports the results from predictive regressions of stock market returns on lagged latent variables. Stock market returns are proxed by the excess returns of the CRSP value-weighted index, taken from Ken French's website. Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2010Q3, and 1975Q1-2010Q3, respectively. Within each panel, the results of an OLS regression where quarterly latent variables predict stock returns of one month ahead, one quarter ahead, and one year ahead are reported, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	NT	IST	MP	$\bar{R}^2(\%)$
		Panel A: 1966Q1 - 2010Q3		
		One-month horizon		
-1.24	302.12	37.20	-547.52	3.08
(-1.48)	(1.81)	(0.63)	(-2.20)	
		One-quarter horizon		
-0.04	9.33	1.78	-8.67	4.27
(-2.11)	(3.00)	(1.44)	(-2.23)	
		One-year horizon		
-0.06	15.00	10.39	-28.32	11.14
(-1.35)	(2.03)	(2.57)	(-3.71)	
		Panel B: 1970Q1 - 2010Q3		
		One-month horizon		
-1.44	326.26	39.32	-558.14	3.04
(-1.61)	(1.84)	(0.64)	(-2.10)	
		One-quarter horizon		
-0.04	9.94	1.77	-8.69	4.25
(-2.04)	(2.97)	(1.39)	(-2.09)	
		One-year horizon		
-0.07	17.41	11.17	-28.94	12.62
(-1.58)	(2.46)	(2.73)	(-3.69)	
		Panel C: 1975Q1 - 2010Q3		
		One-month horizon		
-1.37	364.09	34.31	-454.57	1.55
(-1.44)	(2.02)	(0.53)	(-1.94)	
		One-quarter horizon		
-0.02	8.39	0.81	-6.36	2.07
(-1.30)	(2.51)	(0.66)	(-1.47)	
		One-year horizon		
-0.05	18.09	8.81	-21.25	7.38
(-1.12)	(2.50)	(1.98)	(-2.44)	

Table 6: **Return Predictability Comparison at One-Month Horizon: Stock Market Returns**

This table reports the results from predictive regressions of stock market returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t. Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict stock returns of one month ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	NT	IST	MP	*cay*	*gap*	$\bar{R}^2$(%)
			Panel A: 1966Q1 - 2010Q3			
-1.24	302.12	37.20	-547.52			3.08
(-1.48)	(1.81)	(0.63)	(-2.20)			
0.48				24.46		0.16
(1.39)				(1.60)		
0.48					-8.26	0.30
(1.41)					(-1.65)	
			Panel B: 1970Q1 - 2010Q3			
-1.44	326.26	39.32	-558.14			3.04
(-1.61)	(1.84)	(0.64)	(-2.10)			
0.41				24.73		0.15
(1.11)				(1.59)		
0.41					-8.25	0.29
(1.12)					(-1.61)	
			Panel C: 1975Q1 - 2010Q3			
-1.37	364.09	34.31	-454.57			1.55
(-1.44)	(2.02)	(0.53)	(-1.94)			
0.54				17.61		-0.29
(1.39)				(1.10)		
0.55					-7.50	0.11
(1.45)					(-1.42)	

Table 7: **Return Predictability Comparison at One-Quarter Horizon: Stock Market Returns**

This table reports the results from predictive regressions of stock market returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t . Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict stock returns of one quarter ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2$(%)
			Panel A: 1966Q1 - 2010Q3			
-0.04	9.33	1.78	-8.67			4.27
(-2.11)	(3.00)	(1.44)	(-2.23)			
0.01				0.70		1.43
(1.94)				(1.99)		
0.01					-0.28	2.89
(2.08)					(-2.52)	
			Panel B: 1970Q1 - 2010Q3			
-0.04	9.94	1.77	-8.69			4.25
(-2.04)	(2.97)	(1.39)	(-2.09)			
0.01				0.72		1.58
(1.93)				(2.01)		
0.01					-0.28	2.86
(2.08)					(-2.46)	
			Panel C: 1975Q1 - 2010Q3			
-0.02	8.39	0.81	-6.36			2.07
(-1.30)	(2.51)	(0.66)	(-1.47)			
0.02				0.49		0.40
(2.34)				(1.41)		
0.02					-0.19	1.15
(2.55)					(-1.70)	

Table 8: **Return Predictability Comparison at One-Year Horizon: Stock Market Returns**

This table reports the results from predictive regressions of stock market returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t . Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict stock returns of one year ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2(\%)$
			Panel A: 1966Q1 - 2010Q3			
-0.06	15.00	10.39	-28.32			11.14
(-1.35)	(2.03)	(2.57)	(-3.71)			
0.05				3.14		8.10
(2.46)				(2.75)		
0.06					-1.04	8.94
(2.88)					(-2.81)	
			Panel B: 1970Q1 - 2010Q3			
-0.07	17.41	11.17	-28.94			12.62
(-1.58)	(2.46)	(2.73)	(-3.69)			
0.06				3.04		7.96
(2.49)				(2.58)		
0.06					-0.98	8.43
(2.93)					(-2.62)	
			Panel C: 1975Q1 - 2010Q3			
-0.05	18.09	8.81	-21.25			7.38
(-1.12)	(2.50)	(1.98)	(-2.44)			
0.07				2.16		4.00
(2.65)				(1.85)		
0.07					-0.74	5.08
(3.18)					(-1.95)	

Table 9: **Return Predictability of Estimated Latent Variables: Long-Term Corporate Bond Returns**

This table reports the results from predictive regressions of long-term corporate bond returns on lagged latent variables. Long-term corporate bond returns are from Ibbotson Associates. Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2010Q3, and 1975Q1-2010Q3, respectively. Within each panel, the results of an OLS regression where quarterly latent variables predict long-term corporate bond returns of one month ahead, one quarter ahead, and one year ahead are reported, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	$\bar{R}^2$(%)
		Panel A: 1966Q1 - 2010Q3		
		One-month horizon		
-0.01	1.87	0.88	-4.31	6.84
(-2.43)	(2.04)	(2.79)	(-2.57)	
		One-quarter horizon		
-0.01	1.63	1.36	-7.28	5.90
(-0.88)	(0.86)	(1.94)	(-3.44)	
		One-year horizon		
-0.01	2.65	5.38	-16.21	8.84
(-0.38)	(0.57)	(2.59)	(-3.16)	
		Panel B: 1970Q1 - 2010Q3		
		One-month horizon		
-0.01	1.96	1.01	-4.79	8.32
(-2.59)	(2.03)	(3.21)	(-2.76)	
		One-quarter horizon		
-0.01	1.21	1.59	-7.74	6.97
(-0.55)	(0.59)	(2.14)	(-3.43)	
		One-year horizon		
0.00	1.52	5.61	-16.18	9.57
(0.04)	(0.30)	(2.49)	(-2.95)	
		Panel C: 1975Q1 - 2010Q3		
		One-month horizon		
-0.01	2.04	0.90	-3.66	3.80
(-2.14)	(2.05)	(2.31)	(-1.81)	
		One-quarter horizon		
-0.00	0.67	1.38	-7.27	4.79
(-0.18)	(0.31)	(1.57)	(-2.59)	
		One-year horizon		
0.01	1.58	4.76	-14.89	5.83
(0.17)	(0.28)	(1.77)	(-2.19)	

Table 10: **Return Predictability Comparison at One-Month Horizon: Long-Term Corporate Bond Returns**

This table reports the results from predictive regressions of long-term corporate bond returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t. Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict long-term corporate bond returns of one month ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2$(%)
			Panel A: 1966Q1 - 2010Q3			
-0.01	1.87	0.88	-4.31			6.84
(-2.43)	(2.04)	(2.79)	(-2.57)			
0.00				0.19		0.79
(0.61)				(1.97)		
0.00					-0.05	0.48
(0.61)					(-1.59)	
			Panel B: 1970Q1 - 2010Q3			
-0.01	1.96	1.01	-4.79			8.32
(-2.59)	(2.03)	(3.21)	(-2.76)			
0.00				0.20		0.95
(0.37)				(2.03)		
0.00					-0.06	0.66
(0.38)					(-1.71)	
			Panel C: 1975Q1 - 2010Q3			
-0.01	2.04	0.90	-3.66			3.80
(-2.14)	(2.05)	(2.31)	(-1.81)			
0.00				0.15		0.21
(0.33)				(1.47)		
0.00					-0.04	0.15
(0.41)					(-1.34)	

Table 11: **Return Predictability Comparison at One-Quarter Horizon: Long-Term Corporate Bond Returns**

This table reports the results from predictive regressions of long-term corporate bond returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t . Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict long-term corporate bond returns of one quarter ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2$(%)
			Panel A: 1966Q1 - 2010Q3			
-0.01	1.63	1.36	-7.28			5.90
(-0.88)	(0.86)	(1.94)	(-3.44)			
0.01				0.25		0.14
(1.79)				(1.25)		
0.01					-0.18	3.05
(1.99)					(-2.95)	
			Panel B: 1970Q1 - 2010Q3			
-0.01	1.21	1.59	-7.74			6.97
(-0.55)	(0.59)	(2.14)	(-3.43)			
0.01				0.23		-0.03
(2.25)				(1.10)		
0.01					-0.17	2.93
(2.50)					(-2.89)	
			Panel C: 1975Q1 - 2010Q3			
-0.00	0.67	1.38	-7.27			4.79
(-0.18)	(0.31)	(1.57)	(-2.59)			
0.01				0.13		-0.52
(2.18)				(0.62)		
0.01					-0.15	1.93
(2.39)					(-2.44)	

Table 12: **Return Predictability Comparison at One-Year Horizon: Long-Term Corporate Bond Returns**

This table reports the results from predictive regressions of long-term corporate bond returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t . Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict long-term corporate bond returnsof one year ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2$(%)
			Panel A: 1966Q1 - 2010Q3			
-0.01	2.65	5.38	-16.21			8.84
(-0.38)	(0.57)	(2.59)	(-3.16)			
0.03				1.01		2.05
(2.11)				(1.66)		
0.03					-0.61	9.36
(2.25)					(-3.01)	
			Panel B: 1970Q1 - 2010Q3			
0.00	1.52	5.61	-16.18			9.57
(0.04)	(0.30)	(2.49)	(-2.95)			
0.04				0.90		1.63
(2.61)				(1.49)		
0.04					-0.58	9.15
(2.79)					(-2.88)	
			Panel C: 1975Q1 - 2010Q3			
0.01	1.58	4.76	-14.89			5.83
(0.17)	(0.28)	(1.77)	(-2.19)			
0.04				0.55		0.12
(2.49)				(0.90)		
0.04					-0.51	6.88
(2.66)					(-2.46)	

Table 13: **Return Predictability of Estimated Latent Variables: Long-Term Government Bond Returns**

This table reports the results from predictive regressions of long-term government bond returns on lagged latent variables. Long-term government bond returns are from Ibbotson Associates. Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2010Q3, and 1975Q1-2010Q3, respectively. Within each panel, the results of an OLS regression where quarterly latent variables predict long-term government bond returns of one month ahead, one quarter ahead, and one year ahead are reported, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	$\bar{R}^2$(%)
		Panel A: 1966Q1 - 2010Q3		
		One-month horizon		
-0.01	1.92	1.08	-2.95	3.22
(-2.67)	(1.84)	(3.10)	(-1.64)	
		One-quarter horizon		
-0.01	1.26	1.03	-5.75	2.55
(-0.48)	(0.54)	(1.41)	(-2.52)	
		One-year horizon		
-0.02	5.48	4.16	-11.13	3.33
(-0.57)	(1.07)	(1.71)	(-2.05)	
		Panel B: 1970Q1 - 2010Q3		
		One-month horizon		
-0.02	2.13	1.20	-3.59	4.59
(-2.90)	(1.95)	(3.45)	(-1.94)	
		One-quarter horizon		
-0.00	1.18	1.30	-6.49	3.58
(-0.35)	(0.48)	(1.73)	(-2.70)	
		One-year horizon		
-0.00	4.48	4.34	-11.24	3.50
(-0.13)	(0.81)	(1.70)	(-1.91)	
		Panel C: 1975Q1 - 2010Q3		
		One-month horizon		
-0.02	2.09	1.24	-2.81	2.73
(-2.41)	(1.80)	(2.77)	(-1.24)	
		One-quarter horizon		
-0.00	1.00	1.14	-5.95	1.77
(-0.13)	(0.37)	(1.25)	(-1.96)	
		One-year horizon		
0.00	4.91	3.44	-9.33	0.95
(0.02)	(0.80)	(1.11)	(-1.26)	

Table 14: **Return Predictability Comparison at One-Month Horizon: Long-Term Government Bond Returns**

This table reports the results from predictive regressions of long-term government bond returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t. Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict long-term government bond returns of one month ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2$(%)
			Panel A: 1966Q1 - 2010Q3			
-0.01	1.92	1.08	-2.95			3.22
(-2.67)	(1.84)	(3.10)	(-1.64)			
-0.00				0.25		1.47
(-0.23)				(2.53)		
-0.00					0.01	-0.54
(-0.22)					(0.22)	
			Panel B: 1970Q1 - 2010Q3			
-0.02	2.13	1.20	-3.59			4.59
(-2.90)	(1.95)	(3.45)	(-1.94)			
-0.00				0.26		1.64
(-0.36)				(2.57)		
-0.00					0.00	-0.61
(-0.31)					(0.07)	
			Panel C: 1975Q1 - 2010Q3			
-0.02	2.09	1.24	-2.81			2.73
(-2.41)	(1.80)	(2.77)	(-1.24)			
-0.00				0.24		1.10
(-0.32)				(2.06)		
-0.00					0.02	-0.61
(-0.13)					(0.37)	

Table 15: **Return Predictability Comparison at One-Quarter Horizon: Long-Term Government Bond Returns**

This table reports the results from predictive regressions of long-term government bond returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t . Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict long-term government bond returns of one quarter ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2(\%)$
			Panel A: 1966Q1 - 2010Q3			
-0.01	1.26	1.03	-5.75			2.55
(-0.48)	(0.54)	(1.41)	(-2.52)			
0.01				0.23		-0.04
(1.70)				(1.12)		
0.01					-0.09	0.28
(1.76)					(-1.26)	
			Panel B: 1970Q1 - 2010Q3			
-0.00	1.18	1.30	-6.49			3.58
(-0.35)	(0.48)	(1.73)	(-2.70)			
0.01				0.20		-0.21
(2.19)				(0.96)		
0.01					-0.09	0.17
(2.26)					(-1.18)	
			Panel C: 1975Q1 - 2010Q3			
-0.00	1.00	1.14	-5.95			1.77
(-0.13)	(0.37)	(1.25)	(-1.96)			
0.01				0.10		-0.61
(2.13)				(0.46)		
0.01					-0.06	-0.31
(2.21)					(-0.82)	

Table 16: **Return Predictability Comparison at One-Year Horizon: Long-Term Government Bond Returns**

This table reports the results from predictive regressions of long-term government bond returns at one-month horizon on lagged latent variables, the *cay* factor (Lettau and Ludvigson, 2001), and output gap (Cooper and Priestley, 2009). The *cay* factor is constructed using data from Sidney Ludvigson's website. The output gap is the residual μ_t from the following regression over the 1966m01 and 2010m09 sample: $y_t = a + b \cdot t + c \cdot t^2 + \mu_t$, where y_t is the log of industrial production at month t . Panels A, B and C present the results for three data periods, 1966Q1-2010Q3, 1970Q1-2005Q4, and 1975Q1-2005Q4, respectively. Within each panel, the results of an OLS regression where quarterly latent shocks, the *cay* factor, and the *gap*, predict long-term government bond returnsof one year ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	*NT*	*IST*	*MP*	*cay*	*gap*	$\bar{R}^2$
			Panel A: 1966Q1 - 2010Q3			
-0.02	5.48	4.16	-11.13			3.33
(-0.57)	(1.07)	(1.71)	(-2.05)			
0.03				0.95		1.61
(1.97)				(1.49)		
0.03					-0.35	2.46
(1.99)					(-1.79)	
			Panel B: 1970Q1 - 2010Q3			
-0.00	4.48	4.34	-11.24			3.50
(-0.13)	(0.81)	(1.70)	(-1.91)			
0.04				0.84		1.20
(2.54)				(1.35)		
0.04					-0.32	2.19
(2.57)					(-1.63)	
			Panel C: 1975Q1 - 2010Q3			
0.00	4.91	3.44	-9.33			0.95
(0.02)	(0.80)	(1.11)	(-1.26)			
0.04				0.52		-0.04
(2.47)				(0.83)		
0.04					-0.25	0.96
(2.52)					(-1.23)	

Table 17: **Return Predictability Comparison with Financial Variables: Stock Market Returns**

This table reports the results from predictive regressions of stock market returns on lagged latent variables and financial variables including *dividend price ratio* (d/p), *earnings price ratio* (e/p), *default yield spread* (dfy), *term spread* (tms). Data of financial variables are taken from Amit Goyal's website. Panels A, B and C present the results of an OLS regression for period 1966Q1-2010Q3 where quarterly explanatory variables predict long-term government bond returns of one month ahead, one quarter ahead, and one year ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	NT	IST	MP	d/p	e/p	dfy	tms	$\bar{R}^2(\%)$
				Panel A: One-month horizon				
-1.24	302.12	37.20	-547.52					3.08
(-1.48)	(1.81)	(0.63)	(-2.20)					
-1.01				48.28				0.69
(-0.99)				(1.51)				
-0.83					19.78			0.68
(-0.83)					(1.36)			
-0.62						101.98		0.25
(-0.64)						(1.10)		
0.30							10.37	-0.47
(0.55)							(0.43)	
				Panel B: One-quarter horizon				
-0.04	9.33	1.78	-8.67					4.27
(-2.11)	(3.00)	(1.44)	(-2.23)					
-0.01				0.80				0.64
(-0.62)				(1.40)				
-0.00					0.21			-0.09
(-0.04)					(0.84)			
-0.01						1.97		0.49
(-0.42)						(1.04)		
-0.00							0.73	1.06
(-0.01)							(1.67)	
				Panel C: One-year horizon				
-0.06	15.00	10.39	-28.32					11.14
(-1.35)	(2.03)	(2.57)	(-3.71)					
-0.05				3.53				4.71
(-0.81)				(1.89)				
-0.00					0.91			1.51
(-0.06)					(1.18)			
-0.02						7.51		2.95
(-0.44)						(1.55)		
0.01							2.73	4.34
(0.25)							(1.88)	

Table 18: **Return Predictability Comparison with Financial Variables: Long-Term Corporate Bond Returns**

This table reports the results from predictive regressions of long-term corporate bond returns on lagged latent variables and financial variables including *dividend price ratio* (d/p), *earnings price ratio* (e/p), *default yield spread* (dfy), *term spread* (tms). Data of financial variables are taken from Amit Goyal's website. Panels A, B and C present the results of an OLS regression for period 1966Q1-2010Q3 where quarterly explanatory variables predict long-term government bond returns of one month ahead, one quarter ahead, and one year ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	NT	IST	MP	d/p	e/p	dfy	tms	$\bar{R}^2$(%)
				Panel A: One-month horizon				
-0.01	1.87	0.88	-4.31					6.84
(-2.43)	(2.04)	(2.79)	(-2.57)					
-0.00				0.15				-0.21
(-0.46)				(0.61)				
-0.00					0.04			-0.41
(-0.19)					(0.35)			
0.01						-0.43		-0.12
(0.76)						(-0.53)		
-0.00							0.20	0.54
(-0.56)							(1.12)	
				Panel B: One-quarter horizon				
-0.01	1.63	1.36	-7.28					5.90
(-0.88)	(0.86)	(1.94)	(-3.44)					
0.00				0.10				-0.52
(0.35)				(0.24)				
0.01					-0.05			-0.49
(0.99)					(-0.29)			
-0.00						0.77		-0.13
(-0.10)						(0.66)		
-0.01							0.85	5.30
(-1.33)							(2.95)	
				Panel C: One-year horizon				
-0.01	2.59	5.35	-15.86					8.49
(-0.40)	(0.55)	(2.58)	(-3.09)					
0.03				0.09				-0.57
(0.60)				(0.06)				
0.06					-0.43			0.70
(1.45)					(-0.64)			
-0.03						5.74		4.95
(-1.06)						(1.81)		
-0.03							3.39	19.84
(-1.81)							(4.95)	

Table 19: **Return Predictability Comparison with Financial Variables: Long-Term Government Bond Returns**

This table reports the results from predictive regressions of long-term government bond returns on lagged latent variables and financial variables including *dividend price ratio* (d/p), *earnings price ratio* (e/p), *default yield spread* (dfy), *term spread* (tms). Data of financial variables are taken from Amit Goyal's website. Panels A, B and C present the results of an OLS regression for period 1966Q1-2010Q3 where quarterly explanatory variables predict long-term government bond returns of one month ahead, one quarter ahead, and one year ahead, respectively. The Newey-West corrected t-statistics are reported in parentheses and $\bar{R}^2$ is the adjusted R^2.

constant	NT	IST	MP	d/p	e/p	dfy	tms	$\bar{R}^2(\%)$
				Panel A: One-month horizon				
-0.01	1.92	1.08	-2.95					3.22
(-2.67)	(1.84)	(3.10)	(-1.64)					
-0.00				0.05				-0.52
(-0.30)				(0.23)				
-0.00					0.07			-0.19
(-0.61)					(0.56)			
0.01						-1.15		2.22
(1.30)						(-1.23)		
-0.00							0.14	-0.14
(-0.79)							(0.71)	
				Panel B: One-quarter horizon				
-0.01	1.26	1.03	-5.75					2.55
(-0.48)	(0.54)	(1.41)	(-2.52)					
0.01				-0.06				-0.55
(0.75)				(-0.15)				
0.01					-0.01			-0.57
(0.72)					(-0.06)			
0.01						-0.19		-0.54
(0.76)						(-0.16)		
-0.01							0.77	3.76
(-1.13)							(2.65)	
				Panel C: One-year horizon				
-0.02	5.44	4.11	-10.75					3.07
(-0.57)	(1.05)	(1.68)	(-1.97)					
0.05				-0.60				-0.20
(1.14)				(-0.41)				
0.05					-0.36			0.27
(1.38)					(-0.58)			
0.01						1.41		-0.27
(0.33)						(0.42)		
-0.03							3.03	14.64
(-1.54)							(4.07)	

Figure 1: **Estimated Latent Variables**

This figure plots the estimated latent variables: total factor productivity μ_z, investment-specific technology μ_ψ, and monetary policy shock μ_V for sample period 1966Q1 - 2010Q3.

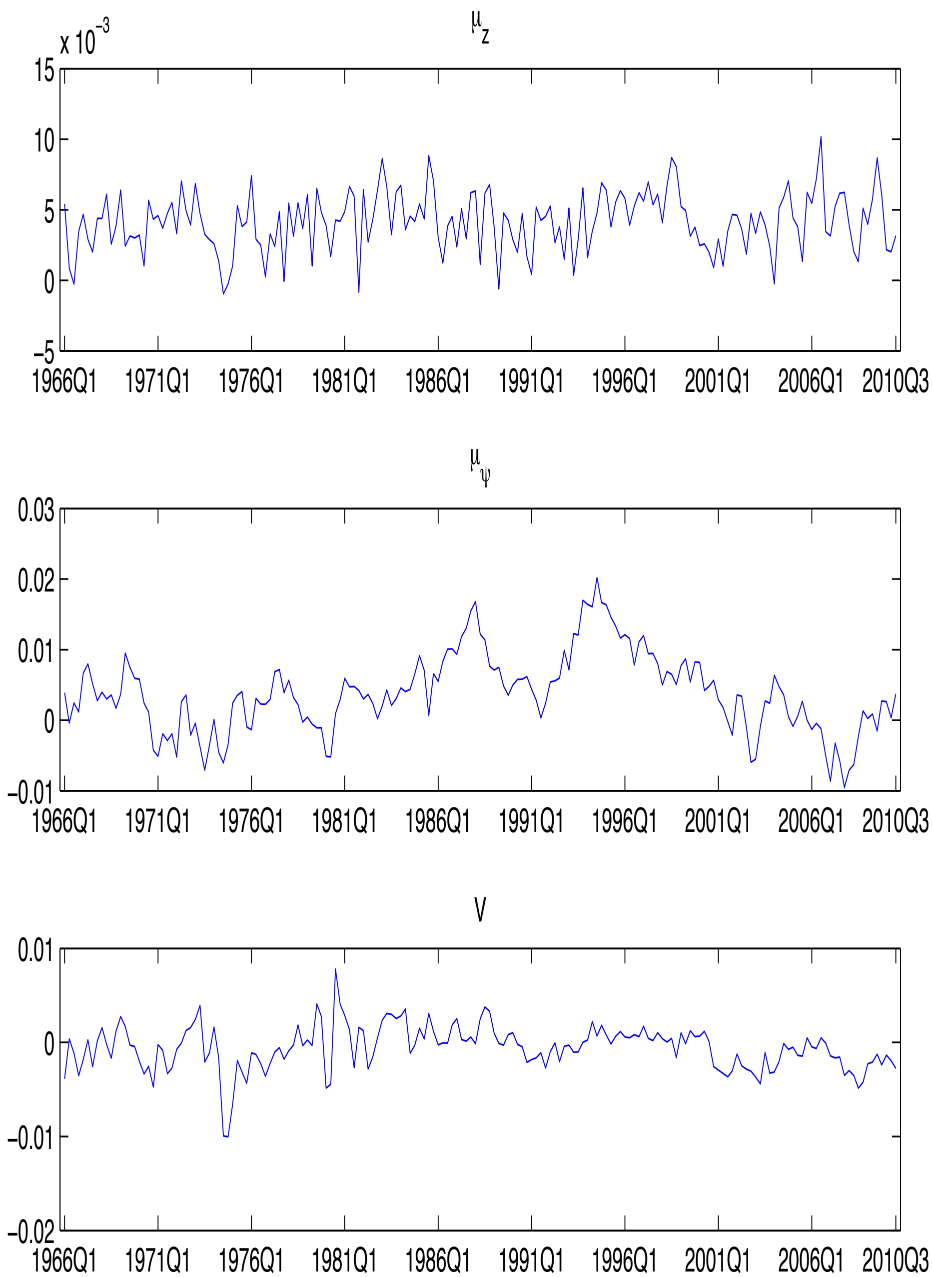

Figure 2: **Impulse Response Functions of NT Shock**

This figure plots the impulse response functions of consumption growth (Δc), pricing kernel (m), dividend growth (Δd), price-dividend ratio (Pd), excess stock return (R), and expected stock return of next period ($E(R)$), in response to a Neutral Technology (NT) shock with magnitude of σ_z.

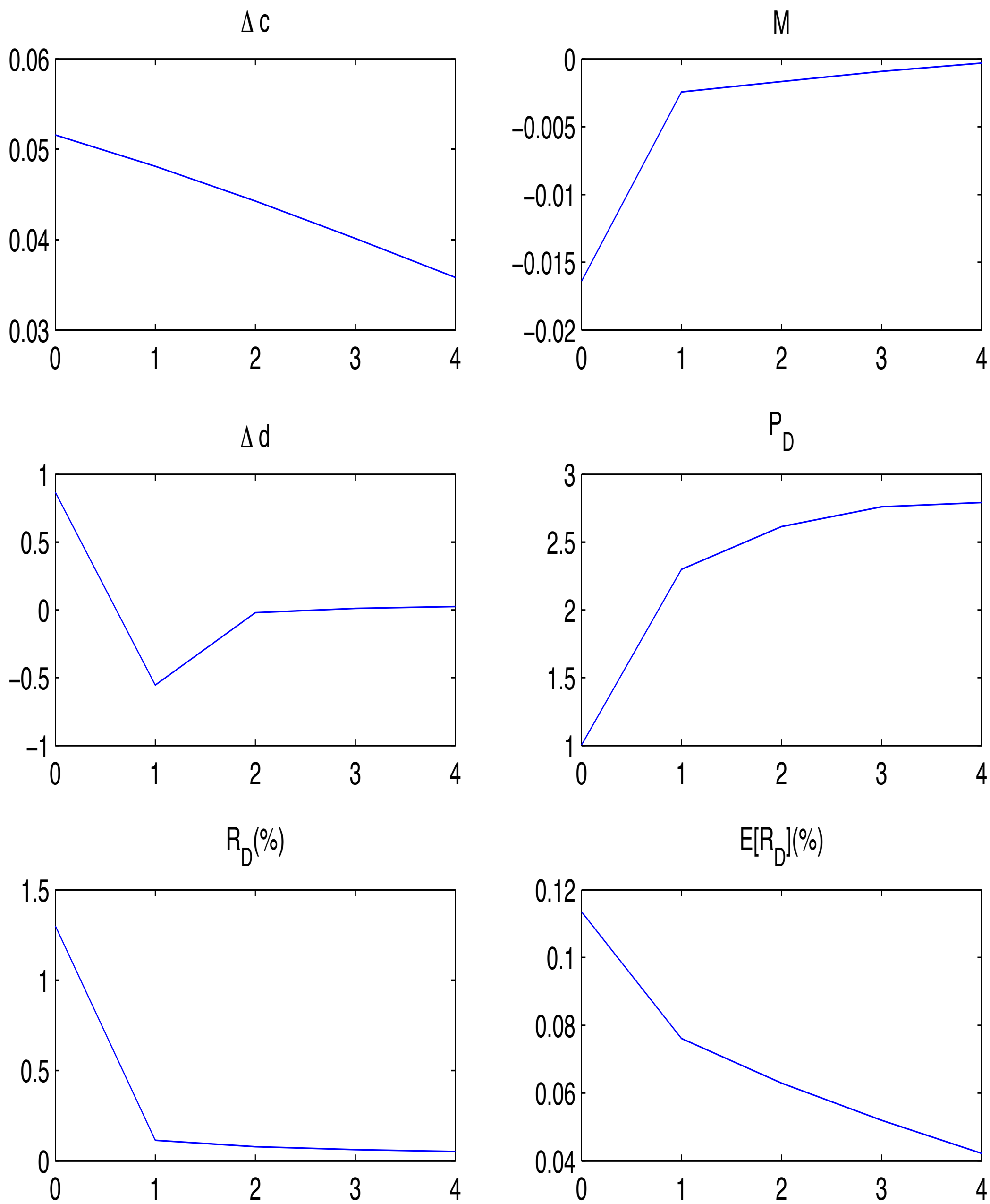

Figure 3: **Impulse Response Functions of IST Shock**

This figure plots the impulse response functions of consumption growth (Δc), pricing kernel (m), dividend growth (Δd), price-dividend ratio (Pd), excess stock return (R), and expected stock return of next period ($E(R)$), in response to an investment-Specific Technological (IST) shock with magnitude of σ_{ψ}.

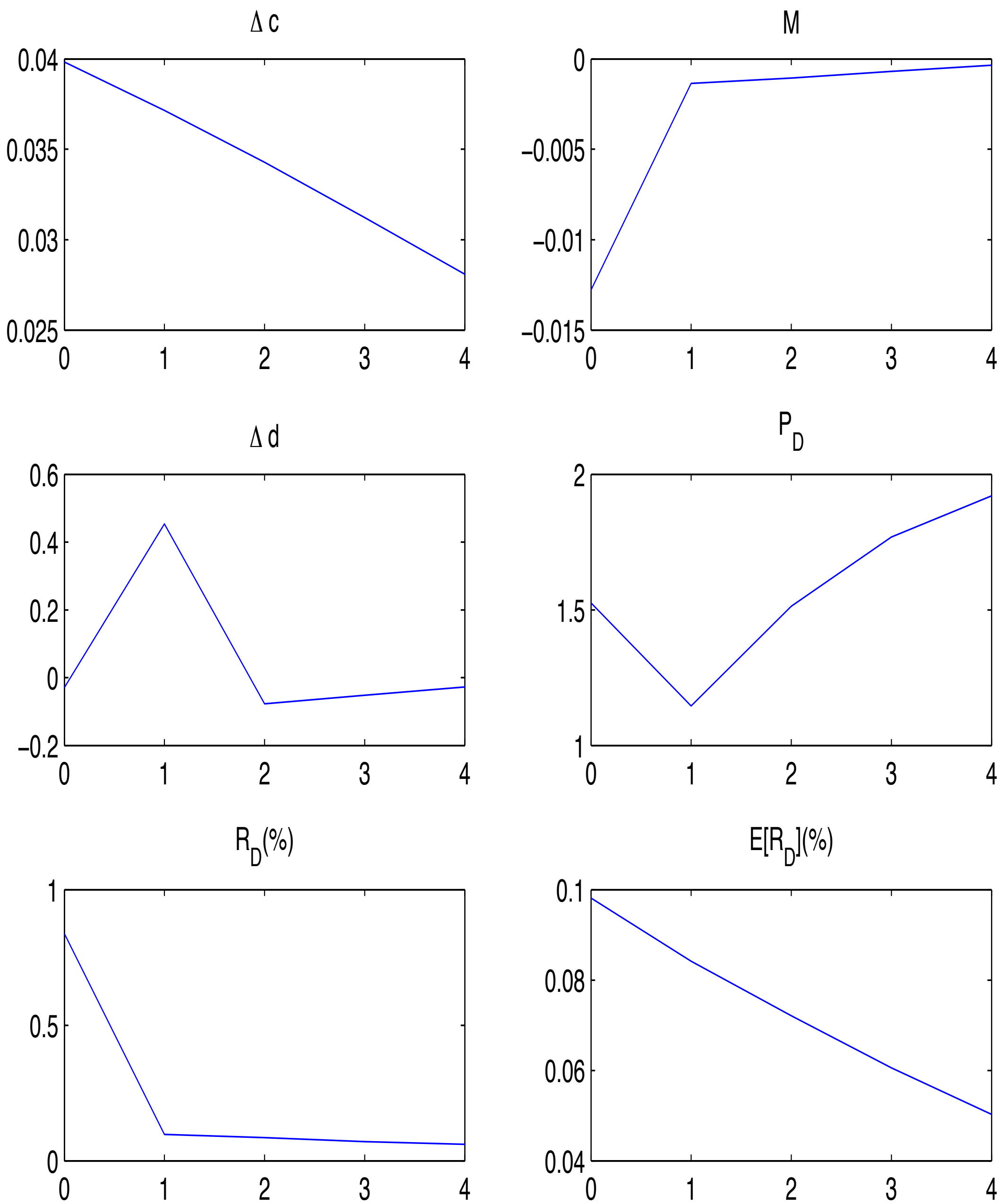

Figure 4: **Impulse Response Functions of MP Shock**

This figure plots the impulse response functions of consumption growth (Δc), pricing kernel (m), dividend growth (Δd), price-dividend ratio (Pd), excess stock return (R), and expected stock return of next period ($E(R)$), in response to a Monetary Policy (MP) shock with magnitude of σ_v.

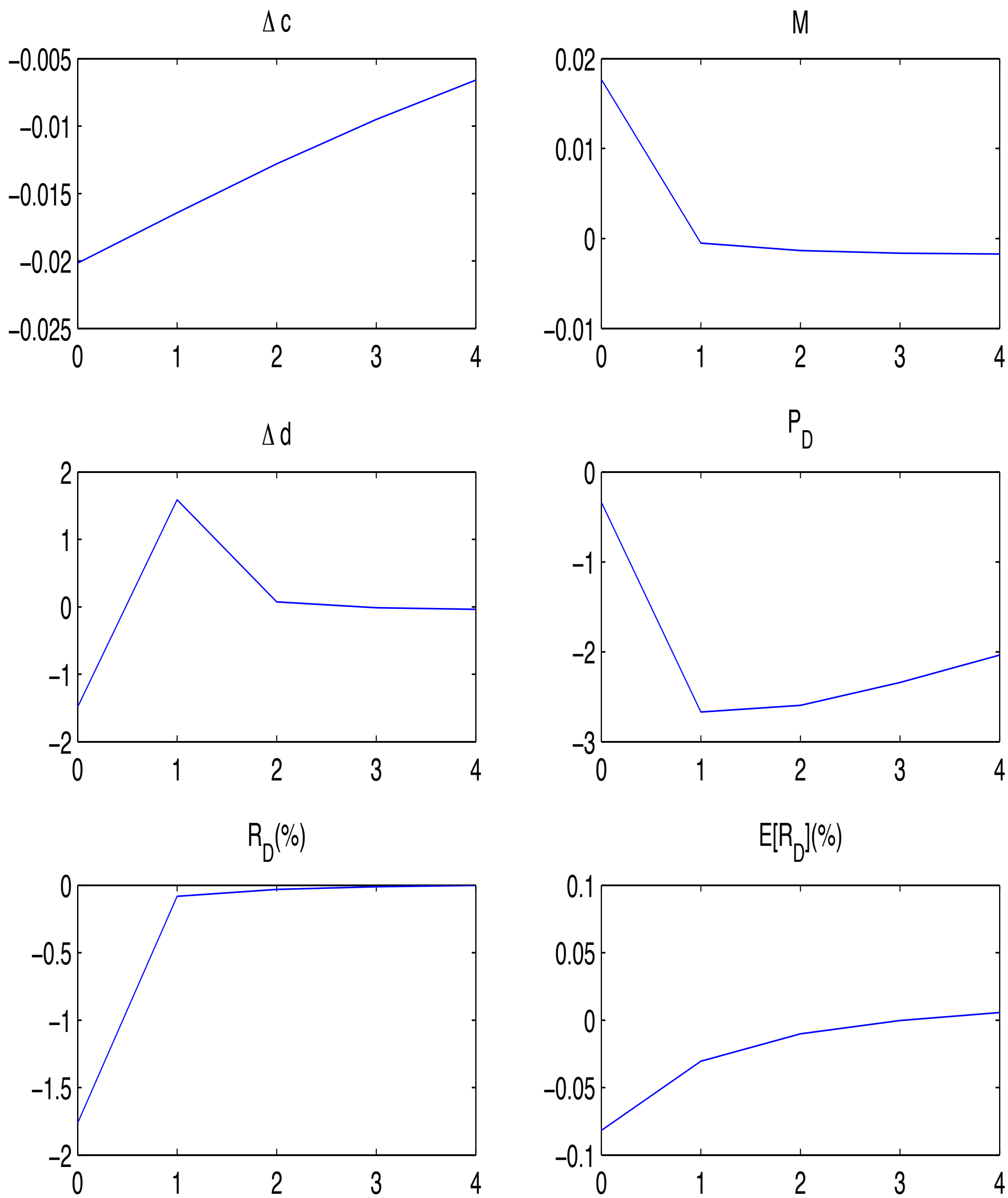

Figure 5: **Loadings of Size, Book-t-Market, and AG Portfolios to The Mimicking Portfolios of Three Latent Shocks**

The figure plots the beta loadings of 10 equal-weighted size portfolios, 10 equal-weighted book-to-market portfolios, and 10 equal-weighted asset growth portfolios on the mimicking portfolios of NT shock, IST shock, and MP sock.