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 dynamic stochastic general equilibrium (DSGE) model. We provide full-information Bayesian estimation of the DSGE model using macroeconomic variables and extract the time-series of four latent fundamental shocks of the model: neutral technology shock, investment-specific technological shock, monetary policy shock, and risk shock. Asset pricing tests show that our model-implied four-factor model can explain a number of prominent cross-sectional return spreads: size, book-to-market, investment, earnings, and long-term reversal. The investment-specific technological shock and risk shock play the most important role in explaining those return spreads.

Keywords: DSGE model, Bayesian MCMC estimation, stock returns, neutral technology shock, investment-specific technology shock, monetary policy shock, risk shock

JEL Classification: C11, C13, E44

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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 (Cochrane, 2005). 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 (Dai and Singleton, 2003) also mainly focus on the relative pricing of bonds across maturities by assuming that the yield curve is driven by some latent state variables without explicitly modeling their economic nature.

Researchers have been paying increasing attention in relating asset prices to economic fundamentals as evidenced by the rapid growth of the macro-finance literature. For example, by incorporating the Taylor rule into traditional term structure models, Ang and Piazzesi (2003), among others, show that inflation and output gap can explain a significant portion of the fluctuations of bond yields. The investment-based asset pricing literature has also tried to relate equity returns to firm fundamentals, thus giving economic meanings to empirical-based factors (such as the size and book-to-market factors) for equity returns (Zhang, 2005).

The New Keynesian Dynamic Stochastic General Equilibrium (DSGE) models offer a unified framework to examine the link between asset prices and economic fundamentals. As a well-established modeling framework in macroeconomics, DSGE models have been widely used by academics and central banks around the world for policy analysis (Clarida, Galí, and Gertler, 2000 and Galí and Gertler, 2007). However, most existing studies on DSGE models in the macroeconomic literature, such as Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), have mainly focused on the ability of DSGE models in explaining macroeconomic dynamics. If the fundamental shocks identified by DSGE models represent true economic risks, these shocks should also impact asset prices because financial assets represent claims on real productive assets. Therefore, whether these shocks impact asset prices provides a natural test on DSGE models. Moreover, since asset prices are forward looking and contain market expectations for future economic activities, the identification of model parameters and latent shocks might be significantly improved by incorporating asset prices into the estimation of DSGE models.

In this paper, we study the link between macroeconomic fundamentals and asset pricing through the lens of a New Keynesian DSGE model. Our model is based on the framework in Christiano, Motto, and Rostagno (2014) (CMR). An important contribution of CMR is to introduce risk shock into DSGE models and show that risk shock is the most important shocks driving the business cycle. Risk shock is first introduced in Bernanke, Gertler, and Gilchrist (1999). In the presence of risk shock, credit market frictions play a quantitatively important role in shaping business cycle dynamics. A group of agents, called entrepreneurs, combine their own wealth with bank loans to acquire raw capital and transform it into effective capital. There is idiosyncratic uncertainty in the efficacy of this transformation by each entrepreneur and this uncertainty exhibits a cross-sectional dispersion. The change in the magnitude of this dispersion is referred to as the risk shock. CMR show that DSGE models can match a wide range of macroeconomic variables well, including fluctuations in the credit market. We modify the power utility preference of household in CMR with a recursive preference with habit formation so that the model has the potential to generate quantitatively relevant implications on asset prices.

We estimate the DSGE model using nine macroeconomic variables: per capita output growth, per capita consumption growth, per capita investment growth, average weekly hours per capita, growth rate of relative price of consumption to investment goods, inflation, 3-month T-bill rate, growth rate of credit supply, and credit spread between BAA corporate bonds and 10 year treasury bonds. Whereas most estimations in the literature essentially match the unconditional moments of the macroeconomic variables, we consider the full-information Bayesian Markov Chain Monte Carlo (MCMC) method that fully exploits the conditional information in the likelihood function of the macroeconomic data. As a result, our method not only provides more efficient estimation of model parameters but also makes it possible to back out the four latent economic shocks: neutral technology (NT) shock, investment-specific technological (IST) shock, monetary policy (MP) shock, and risk (Risk) shock. In contrast, the Bayesian moment-matching methods cannot back out the latent shocks, because they only match the long-run average features of the data.

We study whether the four fundamental economic shocks implied by our model have any explanatory power for the cross-sectional returns of a wide range of financial assets. We first estimate the risk premia of our model-implied shocks using the widely used two-step Fama and MacBeth (1973) cross-sectional regression methodology. We show that in univariate models, the NT shock has a significant and positive risk premium. The IST, MP, and Risk shocks have significant and negative risk premia. The empirically estimated risk premia have the same signs as predicted by the model. In the four-factor multivariate model, the risk premia of IST and Risk shocks remain negative and significant, while the risk premia of NT and MP shocks become insignificant. This result suggests that in the horse race among the four shocks, IST and Risk shocks play a more important role during our sample period.

We then estimate the betas of several prominent characteristics-based test asset returns, such as the size and book-to-market decile portfolios, with respect to the four model implied shocks. We show that small firms load more on the NT shock and load less on the IST, MP, and Risk shocks; high book-to-market firms load less on all four shocks than low book-to-market firms do. The pattern of shock loadings is consistent with our conjecture based on the economic interpretations of these shocks.

Finally, based on our estimated risk premia and betas, we compute the expected returns for a number of prominent cross-sectional return spreads: size, book-to-market, investment, earnings, momentum, and long-term reversal. Following the standard practice (Cooper and Priestley, 2011; Garlappi and Song, 2016a), we calculate the expected return as the summation of expected risk premia from the four model-implied shocks, $ER = \sum_i \beta_i \lambda_i$, $i = NT,\ IST,\ MP$, and $Risk$. We then compute the difference between the actual return and expected returns (R-ER), which is effectively the alphas with respect to our model-implied four-factor model.

The results show that the four model-implied shocks can explain all the aforementioned return spreads except momentum. The alphas of size, book-to-market, investment, earnings, and long-run reversal spreads becomes statistically insignificant and the alpha of momentum spread is still significantly positive under our model-implied four-factor model. By comparing our model with a number of return-based factor models in terms of the significance and absolute magnitude of alphas, we show that our model is closest to the Fama-French five factor model in terms of performance. Our model has larger absolute magnitude of size, investment, and earnings alphas but smaller book-to-market, momentum, and long-term reversal alphas than the Fama-French five factor model.

We further identify the role of each shock in explaining these return spreads. We find that, among the four model-implied shocks, the IST and Risk shocks have the strongest explanatory power for the six cross-sectional return spreads, while the NT and MP shocks play less important roles. The IST shock explains 47.8% of size spread, 73.0% of book-to-market spread, 57.1% of investment spread, 41.4% of earnings spread, 28.7% of long-run reversal spread, and 29.7% of momentum spread. The risk shock explains 132.4% of size spread, 42.3% of value spread, 45.8% of earnings spread, and 63.5% of long-run reversal spread.

As a robustness check, we estimate the risk premia of these four shocks based on the sets of test assets without momentum portfolios and find similar results. The estimates of IST risk premium is less sensitive to the inclusion of momentum portfolios than previous study (Garlappi and Song, 2016a) suggests. The difference may lie in the fact that previous studies measure the IST shock using empirical proxies, while we extract the IST shock using full-information Bayesian estimation. This result suggests that the DSGE structure imposed on our estimation helps to filter out noises in the data.

In order to examine how risk premia of these shocks vary over time, we split our sample into two subperiods: the pre-1990 subperiod from 1957q2 to 1989q4 and the post-1990 subperiod from 1990q1 to 2015q4. In general, the signs and significances of the risk premia of the four shocks in univariate regressions are stable across the two subperiods, but are generally not stable in multivariate regressions. The only shock with stable and significant risk premium in both univariate and multivariate regressions is the Risk shock. The IST shock is relatively more important in the pre-1990 period, which is consistent with the finding in Garlappi and Song (2016a) that the risk premium of IST shock is stronger in early times and disappears in recent years. In summary, our results demonstrate the great potential of the DSGE models and Bayesian MCMC method for asset pricing studies. Our empirical exercises also provide a new perspective on how to examine and select DSGE models. Integrating asset pricing and macroeconomics under the DSGE framework is an exciting direction for future research.

Our paper is closely related to Smets and Wouters (2007), who estimate a similar DSGE model with seven latent shocks using the Bayesian MCMC method. However, their focus is to match and forecast macroeconomic dynamics. Moreover, Smets and Wouters (2007) estimate a log-linearized model, which is not suitable for asset pricing studies, while we estimate a model solved to the second-order. Our model setup is the same as the one in CMR. The focus of these papers is on examining the economic mechanisms, such as wage rigidities, working capital, and variable capital utilization, that are important for capturing the observed macroeconomic dynamics. In contrast, our focus is on the cross-sectional asset pricing implications of the DSGE model.

Our paper is also related to the literature that aims to explain asset prices using macroeconomic variables, pioneered by Chen, Roll, and Ross (1986). Ludvigson and Ng (2007) extract risk factors from 209 macroeconomic and 172 financial variables to explain asset prices using principle component analysis while we construct factors based on the structural estimation of a DSGE model. Bernanke and Kuttner (2005), Balvers and Huang (2007), and Kogan and Papanikolaou (2013) study the asset pricing implications of the MP, NT, and IST shocks, respectively. While the three shocks are constructed independently via nonstructural methods in these three papers, our three latent shocks are constructed simultaneously under the general equilibrium framework of the model. Moreover, while they focus on the asset pricing implications of each specific latent shock, our paper focuses more on the potential of DSGE models in capturing asset prices.

The rest of the paper is organized as follows. Section 2 introduces the DSGE model. Section 3 discusses the full-information Bayesian estimation and model implications on asset prices. Section 4 empirically examines the asset pricing implications of the model-implied pricing kernel and risk factors in the cross section. Section 5 checks the robustness of our empirical results. Section 6 concludes.

2 The Model

Our framework follows the one in Christiano, Motto, and Rostagno (2014) (CMR). The model considers an economy with a perfectly competitive final goods market, a monopolistically competitive intermediate goods market, and households that derive utility from final goods consumption and disutility from supplying labor to production. Nominal price and wage rigidities in the intermediate goods market are modeled as in Calvo (1983). There is financial intermediation in the model, which lends bank loans to entrepreneurs. Entrepreneurs combine their own wealth with bank loans to acquire raw capital and transform it into effective capital, which is rented by intermediate goods producers. There is idiosyncratic uncertainty in the efficacy of this transformation by each entrepreneur and this uncertainty exhibits a cross sectional dispersion. We refer to the change in the magnitude of this dispersion as risk shock.Government consumes a fixed fraction of GDP every period and the monetary authority sets the nominal interest rate according to a Taylor rule. There are four types of exogenous shocks in the economy: neutral technology (NT) shocks, investment-specific technological (IST) shocks, monetary policy (MP) shocks, and risk shock (Risk). In what follows, we first present the main elements of the model and then in Section 2.6 we provide a detailed discussion of the model framework. Additional details of the model are in the Online Appendix.

2.1 Production Sector

There are two industries in the production sector: the final goods industry and the 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 the final goods, $Y_{i,t}$ is the amount of intermediate goods i used in the final goods production, which in equilibrium equals the output of intermediate goods i, and λ_f measures the substitutability among different intermediate goods. When λ_f is larger, the intermediate goods are more substitutable. The final goods industry is perfectly competitive. Profit maximization of the final goods producers leads to the demand function for intermediate goods i: $Y_{i,t} = Y_t \left(\frac{P_{i,t}}{P_t} \right)^{\frac{\lambda_f}{\lambda_f - 1}}$, where P_t is the nominal price of the final consumption goods and P_{it} is the nominal price of intermediate goods i.

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

$$Y_{i,t} = \left(z_t H_{i,t}\right)^{1-\alpha} K_{i,t}^{\alpha} - z_t^{+} \varphi \,, \tag{2}$$

where z_t is the level of the neutral technology, $H_{i,t}$ and $K_{i,t}$ are the labor and capital services, respectively, employed by firm i, α is the capital share of the 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 level of the investment-specific technology, measured as the relative price of consumption goods to investment goods. We assume that z_t and Ψ_t evolve as follows:

$$\mu_t^z = \mu_z + \rho_z \mu_{t-1}^z + \sigma_z e_t^z \,, \quad \text{and } \mu_t^z = \Delta \log z_t \,, \, e_t^z \sim \text{IID}\mathcal{N}(0,1) \,, \tag{3}$$

$$\mu_t^{\psi} = \mu_{\psi} + \rho_{\psi} \mu_{t-1}^{\psi} + \sigma_{\psi} e_t^{\psi} \,, \quad \text{and } \mu_t^{\psi} = \Delta \log \Psi_t \,, \, e_t^{\psi} \sim \text{IID}\mathcal{N}(0,1) \,, \tag{4}$$

where e_t^z and e_t^{ψ} are NT and IST shocks, respectively. 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 in the steady state.

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 product in a Calvo (1983) staggered price setting to maximize profits. With probability ξ_p, producer i cannot re-optimize its price and has to set it according to the following rule, $P_{i,t} = \tilde{\pi}_{p,t} P_{i,t-1}$, where $\tilde{\pi}_{p,t} = \left(\pi_t^*\right)^{\ell} \left(\pi_{t-1}\right)^{1-\ell}$ is the inflation indexation, ℓ is a constant between zero and one, π_t^* is the target inflation rate or steady state inflation rate, and $\pi_t \equiv P_t / P_{t-1}$ is the inflation rate. With probability $1 - \xi_p$, producer i sets price $P_{i,t}$ to maximize its profits.

2.2 Labor Unions

There are labor contractors who hire workers of different labor types through labor unions and produce homogenous labor service H_t, according to the following production function:

$$H_t = \left[\int_0^1 h_{jt}^{\frac{1}{\lambda_w}} \, dj\right]^{\lambda_w} , \quad \lambda_w > 1 \,, \tag{5}$$

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, and their profit maximization leads to the demand function for labor type j: $h_{jt} = H_t \left(\frac{W_{jt}}{W_t}\right)^{\frac{-\lambda_w}{\lambda_w - 1}}$. Assume that labor unions face the same Calvo (1983) 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: $W_{jt} = \tilde{\pi}_{w,t} e^{\tilde{\mu}_{w,t}} W_{jt-1}$, where $\tilde{\pi}_{w,t} = (\pi_t^*)^{\ell_w} (\pi_{t-1})^{1-\ell_w}$ is the inflation indexation and $\tilde{\mu}_{w,t} = \ell_\mu \mu_{z^+,t} + (1 - \ell_\mu)\mu_{z^+}$ is the growth indexation. With probability $1 - \xi_w$, labor union j chooses W_{jt}^* to maximize households' utility.

2.3 Households

We assume that there is a continuum of differentiated labor types indexed by j, which is uniformly distributed between zero and one. A typical household has an infinite number of members covering all the labor types. It is assumed that a household's consumption decision is made based on utilitarian basis. That is, every household member consumes the same amount of consumption goods even though they might have different status of employment. A representative household's life-long utility can be written in recursive form:

$$V_t \equiv \max_{\{C_t, L_t, B_t/P_t, I_t\}} \quad (1-\beta)U(C_{h,t}, L_t) + \beta \mathbb{E}_t \left[V_{t+1}^{\frac{1-\gamma}{1-\psi}} \right]^{\frac{1-\psi}{1-\gamma}}$$

and

$$U_t \equiv U(C_{h,t}, L_t) = \frac{C_{h,t}^{1-\psi}}{1-\psi} - A_{L,t} \int_0^1 \frac{L_{jt}^{1+\phi}}{1+\phi} dj,$$

where $C_{h,t}$ is the habit adjusted consumption, defined as $C_{h,t} = C_t - b\bar{C}_{t-1}$, $\bar{C}_{t-1}$ is the aggregate consumption,[1] L_{jt} is the number of household members with labor type j who are employed, β is the discount factor, γ is the constant coefficient of relative risk aversion, ψ is the inverse of the elasticity of intertemporal substitution, and ϕ is the curvature on labor disutility. As shown in Campbell and Cochrane (1999), the effective risk aversion is time-varying in the presence of habit in the preference. The maximization of household life-time utility is subject to the budget

[1]In equilibrium, $C_t = \bar{C}_t$. However, when making decisions, households at time t take $\bar{C}_{t-1}$ as given.

constraint:

$$P_tC_t + B_t + Q_t^k(1-\delta)\bar{K}_{t-1} + \frac{P_t}{\Psi_t}I_t \leq R_{t-1}B_{t-1} + Q_t^k\bar{K}_t + P_tLI_t + P_tD_t + P_tT_t^e\,, \tag{6}$$

where P_t is the price of consumption goods, Q_t^k is the price of raw capital at t, I_t is investment made at t, Ψ_t is the relative price of consumption to investment goods defined later, LI_t is the real wage income defined as $LI_t = \int \frac{W_{j,t}}{P_t}L_{j,t}\,dj$, D_t is the real dividend paid by firms, T_t^e is the net transfer from entrepreneurs, and B_t is the face value of one-period debt lent to entrepreneurs at $t-1$ with gross nominal return R_t, and W_{jt} is the wage rate of labor type j, determined by a monopoly union representing all j-type workers. Households take the wage rate of each labor type as given.

The law of motion for raw capital is given by $\bar{K}_t = (1-\delta)\bar{K}_{t-1} + [1 - S(I_t/I_{t-1})]\,I_t$, where $S(I_t/I_{t-1})I_t$ is the investment adjustment cost (IAC) and $S(x_t)$ is defined by

$$S(x_t) = \frac{\exp\left[\sigma_s\left(x_t - \bar{x}\right))\right] + \exp\left[-\sigma_s\left(x_t - \bar{x}\right)\right]}{2} - 1\,, \tag{7}$$

where $x_t = I_t/I_{t-1}$ and $\bar{x} = \exp(\mu_{z^+} + \mu_\psi)$ is the steady state growth rate of investment. The parameter σ_s is chosen such that $S(\bar{x}) = 0$ and $S'(\bar{x}) = 0$.[2]

2.4 Financial Intermediation

Assume that some members of the representative household are entrepreneurs. They have the ability to turn raw capital into productive capital, which is used in production of intermediate good. The amount of productive capital produced by entrepreneur e depends on his net worth $N_{e,t}$ and a random productive shock $\omega_{e,t}$. Entrepreneurs' productivity $\omega_{e,t}$ follows a lognormal distribution with a constant mean of one and time-varying standard deviation of σ_t, the logarithm of which follows:

$$\ln\left(\frac{\sigma_t}{\bar{\sigma}}\right) = \rho_\sigma \ln\left(\frac{\sigma_{t-1}}{\bar{\sigma}}\right) + \sigma_\sigma e_t^\sigma\,. \tag{8}$$

[2]This formulation of adjustment costs does not allow for zero investment, which leads to infinity. Since zero aggregate investment almost never happens, we can this formulation to match aggregate data. However, this formulation may not be appropriate for firm-level data.

The i.i.d. normal innovation e_t^{σ} is denoted as risk shock. Under the assumption that $\mathbb{E}_{t-1}[\omega_{e,t}] = 1$, the distribution of $\omega_{e,t}$ is $\log(\omega_{e,t}) \sim N(-\sigma_t^2/2, \sigma_t)$.

Let $\chi_{e,t}$ denote the leverage ratio that the entrepreneur can take: $\chi_{e,t} = \frac{N_{e,t}+B_{e,t}}{N_{e,t}}$, where $B_{e,t}$ is the one-period loan to e that matures at $t+1$. In aggregate, we have $N_t = \int_0^1 N_{e,t} d\, e$ and $B_t = \int_0^1 B_{e,t} d\, e$. It can be shown that the leverage ratio χ is the same to all entrepreneurs $\chi_{e,t} = \chi_t = \frac{N_t+B_t}{N_t}$ and $Q_t^k \bar{K}_t = N_t + B_t$, where Q_t^k is the price of raw capital.

Assume that the banking industry is competitive and banks earn risk-free interest rate on loans in every state of $t+1$. Let $\bar{\omega}_{t+1}$ denote the threshold above which entrepreneur is productive enough to pay back the loan. In the event of bankruptcy, μ_b fraction of entrepreneur wealth becomes deadweight loss. R_t^k is the nominal return on raw capital at t from the perspective of entrepreneur, given by

$$R_t^k = \frac{\left[u_t r_t^k - a(u_t)/\Psi_t\right] P_t + (1-\delta) Q_t^k}{Q_{t-1}^k}, \tag{9}$$

and r_t^k is the real rental rate of productive capital paid by producers. The nominal cost of utilization per unit of raw capital is $\frac{P_t}{\Psi_t} a(u_t)$, where $a(u) = r^k[\exp(\sigma_a(u_t - 1)) - 1]/\sigma_a$, and $\sigma_a > 0$. At the end of t, each entrepreneur transfers $1 - \gamma_e$ fraction of his wealth to household and household transfers a fixed amount W_t^e to entrepreneur. The latter serves as an insurance to entrepreneurs so that they have consumptions even if they bankrupt.

2.5 Fiscal and Monetary Authorities

Fiscal authority in the model transfers a fixed fraction g of output as government spending, i.e., $G_t = g Y_t$. The authority sets the level of the short-term nominal interest rate according to the following Taylor rule:

$$\log\left(\frac{R_t}{R}\right) = \rho_R \log\left(\frac{R_{t-1}}{R}\right) + (1-\rho_R)\left[\rho_\pi \log\left(\frac{\pi_t}{\pi}\right) + \rho_y \log\left(\frac{Y_t}{Y}\right)\right] + V_t, \tag{10}$$

where R_t is the short-term nominal interest rate, R, π, and Y are the steady state values for interest rate, inflation, and output, respectively, and V_t is the exogenous component in the Taylor rule, which follows the process:

$$V_t = \rho_V V_{t-1} + \sigma_V e_t^V, \quad e_t^V \sim \text{IID}\mathcal{N}(0,1)\,, \tag{11}$$

where e_t^V is the MP shock.

We complete the description of the model with the two market clearing condition. The first is the resource constraint: $Y_t = C_t + G_t + \frac{I_t}{\Psi_t} + \frac{a(u_t)\bar{K}_{t-1}}{\Psi_t}$. The second condition clears the bond market: $\mathbb{E}_t[M_{t,t+1}R_t] = 1$. Through the pricing kernel $M_{t,t+1}$, the MP shock to interest rate R_t affect economic activities such as output, investment, and consumption.

2.6 Asset Pricing Implications

While researchers have mainly focused on the ability of DSGE models to capture macroeconomic dynamics, these models also have clear asset pricing implications. Specifically, the utility maximization of a representative household in our model leads to the following SDF:

$$M_{t,t+1} = \beta_t \left(\frac{C_{h,t+1}}{C_{h,t}}\right)^{-\psi} \left(\frac{V_{t+1}^{1/(1-\psi)}}{\mathbb{E}_t\left[V_{t+1}^{(1-\gamma)/(1-\psi)}\right]^{1/(1-\gamma)}}\right)^{\psi-\gamma}. \tag{12}$$

The model-implied SDF should price any financial assets. That is, the return on any asset i at $t+1$, R_{it+1}, must satisfy the following Euler equation: $\mathbb{E}_t\left[R_{it+1}M_{t+1}\right] = 1$. For example, the price of a risk-free zero-coupon bond with maturity n and principal of one can be defined recursively

$$P_t^{(n)} = \mathbb{E}_t[M_{t,t+1}P_{t+1}^{(n-1)}]\,. \tag{13}$$

and the yield of the bond is given by $\iota_t^{(n)} = -\ln\left(P_t^{(n)}\right)/n$. We use this definition to compute the interest rate of 10-year government bond used in the estimation.

Following Papanikolaou (2011), we define the price of risk of a random variable e as the Sharpe ratio of a security whose payoff is perfectly correlated with realizations of e. Under this definition, the price of risk of shock e is given by

$$\lambda_{e,t} = -\frac{\mathrm{cov}_t(M_{t,t+1}, e_{t+1})}{\mathbb{E}_t[M_{t,t+1}]\sigma_t(e_{t+1})} = -\rho_{me}\frac{\sigma_t(M_{t,t+1})}{\mathbb{E}_t[M_{t,t+1}]}\,. \tag{14}$$

Hence, the price of risk associated with shock e depends on how the pricing kernel M is correlated with the shock. If the pricing kernel is lower (higher) after an increase in e, then this shock will carry a positive (negative) risk premium. We exam the correlation of M and all four shocks in the estimated model in Section 3.4.

2.7 Discussions on The Model Framework

Preference — Our model follows the framework in CMR except for one crucial difference, the preference.[3] In CMR, households have a preference of power utility with habit formation, which is the special case in our model with $1/\psi = \gamma$. We adopt a more flexible form of preference, Epstein-Zin preference with habit formation, and let the data to determine the parameter values in the preference. Dew-Becker (2014) shows that recursive preference with habit formation in a DSGE framework helps to match the term structure in the data. We choose such a preference to give our model the best chance to generate quantitatively plausible asset pricing implications.

Monopolistically competitive firms – The key feature of the New Keynesian model is its assumption that there are price-setting frictions for products and labor services. These frictions are introduced to generate the inertia in inflation observed in the data. The presence of price-setting frictions requires that firms have the power to set prices, and this in turn requires the presence of monopoly power. The Dixit-Stiglitz (Dixit and Stiglitz, 1977) framework of production is a neat way to handle infinite many monopolistic firms whose products are imperfect substitutes. By using the Dixit-Stiglitz framework in the production of final goods and of labor services, we are able to generate individual downward sloping demand function for each intermediate goods and each labor type. This setup hence gives those intermediate sector firms and labor unions the power to set their own prices or wages. The Calvo stickiness (Calvo, 1983) is just one way to introduce price or wage setting frictions at individual firm or labor union level. Alternatively,

[3]Another difference is that CMR have 12 aggregate shocks but found that most of them do not contribute to the variations of the macroeconomic variables of interest.

the presence of price or wage adjustment costs (Hopenhayn and Rogerson, 1993) can generate the same frictions. Both setups are commonly used in the literature. Moreover, recent studies (Li and Palomino, 2014; Lin and Favilukis, 2016) show that price and wage frictions have important implications on the magnitude of equity premium and on the cross-sectional return patterns. The presence of price and wage stickiness potentially makes the model more relevant to asset pricing.

Investment adjustment costs (IAC) — Our specification of investment adjustment costs in equation (7) is different from the one commonly used in the finance literature:

$$\frac{\sigma_s}{2}\left(\frac{I_t}{K_t}-\delta\right)^2 K_t\,, \tag{15}$$

where IAC is quadratic in investment-to-capital ratio and linear in the level of capital.[4] Specification (15) has a long history in macroeconomics, and has been in use since at least Lucas and Prescott (1971). However, DSGE models have generally abandoned this specification (Christiano, Trabandt, and Walentin, 2011) for the following reason. Empirical evidence suggests that after a negative MP shock, both nominal and real interest rate goes down and aggregate investment goes up in a hump-shaped manner. However, under specification (15), the largest increase in investment happens at the time of the shock because as capital level gets higher, investment becomes increasingly costly. On the contrary, under our specification (7), a quick rise in investment from the previous level is expensive and investment increases gradually.

3 Full-Information Bayesian MCMC Estimation

The Bayesian MCMC method makes it possible to estimate both model parameters and the latent economic shocks by fully exploiting the conditional information contained in the likelihood function of the macroeconomic data. In this section, we discuss the data used in the estimation, the

[4]The second-order Taylor expansion of the IAC defined by equation (7) is quadratic in investment growth rate and linear in investment level:

$$S(I_t/I_{t-1})I_t \approx \frac{\sigma_s}{2}\left(\frac{I_t}{I_{t-1}}-\bar{x}\right)^2 I_t\,.$$

Moreover, investment adjustment cost under our specification is symmetric to positive and negative investments due to the fact that $S(x)=S(-x)$.

goodness-of-fit of the estimation, and the economic properties of the model under the estimated parameter values. To conserve space, the detailed description of the full-information Bayesian MCMC is in the Online Appendix.

We use quarterly observations on nine variables covering the period of 1957q2 - 2015q4 to estimate model parameters and exogenous shocks:[5] per capita GDP growth $dy_t = log(Y_t/Y_{t-1})$, per capita consumption growth $dc = log(C_t/C_{t-1})$, per capita investment growth $di = log(I_t/I_{t-1})$, growth of relative price of investment goods μ_t^{ψ}, inflation π_t, 3-month T-bill rate $r_t = log(R_t)$, weekly hours per capita normalized by sample average $h_t = log(H_t/\bar{H})$, per capita real growth of credit $db_t = log(B_t/(\pi_t * B_{t-1})$, and credit spread $cs_t \equiv Z_t - R_t$.[6]

3.1 Parameters

We partition the model parameters into two sets. Parameters in the first set are calibrated based on the data moments or previous literature. Parameters in the second set are estimated via the Bayesian MCMC method. Following CMR, we fix the depreciation rate δ, the curvature on the disutility of labor ϕ, and the ratio of government spending to GDP at 0.025, 1, and 0.2, respectively. We set the mean growth rates of the neutral technology and the investment specific technology at 0.41 percent and 0.42 percent to match the average growth of per capita real GDP and the average decline of the relative price of investment goods in the sample. We calibrate the discount rate β at 0.994 so that the nonstochastic steady state real interest rate is 2% on an annual basis. Following CMR and Christiano, Eichenbaum, and Evans (2005), we fix the markups in the labor market λ_w and in the product market λ_p at 1.05 and 1.2, respectively. The fraction of entrepreneur wealth transferred to household $(1 - \gamma_e)$ is fixed at $1 - 0.985$ following CMR, which is also close to the value $1 - 0.973$ used in Bernanke, Gertler, and Gilchrist (1999) . We set the steady state default probability $F(\bar{\omega})$ at 0.008, close to 0.0075 in Bernanke, Gertler, and Gilchrist (1999) and 0.0097 in Fisher (1999). The value of bankruptcy cost μ_b is chosen to be 0.3, which is within the range of $0.20 - 0.36$ that Carlstrom and Fuerst (1997) defend as empirically relevant. These calibrated parameter values are reported in Table 1.

[5]The sample of 1956q2 - 2015q4 is the longest sample during which data on the nine macroeconomic variables are available. We use the data during 1956q2 - 1957q1 as the burnin period in our estimation.
[6]The construction and date resources of these nine variables are provided in the Online Appendix.

Table 2 presents the prior means and standard deviations, bounds, and the posterior means and standard deviations of the estimated parameter values. The bounds of the parameters guarantee that the estimated values are economically meaningful. All our estimates fall into the interior of the bounds. Moreover, the posterior modes of all parameters are much greater than the corresponding posterior standard deviations and are highly significant.

The values of economic parameters are largely consistent with the previous literature. Our estimate of wage stickiness is 0.93, implying an average probability of wage change being 7% per quarter. Even though closer to the lower bound, our estimate is still within the range of 5%-18% based on the evidence in Barattieri, Basu, and Gottschalk (2014). The estimate of price stickiness is 0.78, close to 0.74 estimated by CMR. The monetary policy smoothing parameter and policy weights on inflation and output gap are 0.78, 1.55, and 0.63, all of which are in the reasonable range estimated by Clarida, Galí, and Gertler (2000). The posterior mode of the habit parameter is 0.65 and is consistent with the values used in the literature. For example, Constantinides (1990) uses a habit formation level of 0.8, Cochrane and Hansen (1992) use 0.5 and 0.6, and CMR report an estimate of 0.74. The posterior of the constant capital share in the Cobb-Douglas production function is 0.17, which is somewhat lower than the commonly used value of 0.34, suggested by Kydland and Prescott (1982). Finally, the posterior modes of shock volatilities are all in the same order of magnitude as those estimated by CMR. As for the persistences of the shocks, the literature has presented a wide range of possible values depending on the model assumptions and the sample periods. Our estimates are within these ranges.

The three parameters that are most crucial to the model's asset pricing property are the inverse of EIS (ψ), coefficient of relative risk aversion (γ), and the investment adjustment cost parameter (σ_s). The posterior mode of ψ implies an EIS of 1.22, close to the commonly used value of 1.5 in the long-run risk models. The coefficient of relative risk aversion γ has a posterior mode of 5.23, which falls in the middle of the range of reasonable values for risk aversion suggested by Mehra and Prescott (1985). Since EIS$< \gamma$, households prefer early resolution of uncertainty. Our estimate of the investment adjustment cost parameter is 1.48, implying an average adjustment cost-to-output ratio of 0.25%. The number is within the wide range, but close to the lower bound of such costs reported in the empirical literature. For instance, Hall (2004) argues that aggregate investment adjustment costs are close to zero, while Eberly, Rebelo, and Vincentx (2009) report that adjustment costs represent on average 4.6% of firm revenue net of variable costs for Compustat firms.

Kaltenbrunner and Lochstoer (2010) show that high EIS (larger than one) and low investment adjustment cost are necessary in order to generate large risk premium when productivity shocks are permanent. In their calibration, EIS is 1.5, γ is 5, and the investment adjustment costs-to-output ratio is 4%. Since our NT and IST shocks are permanent shocks, the estimated high EIS and low investment adjustment costs give our model the potential to generate larger risk premium even though stock return data is not used in the estimation.

3.2 Goodness-of-Fit of the Model

Figure 1 plots the time series of model-implied macroeconomic variables and their observed counterparts, in red and blue lines, respectively. The model-implied output growth (dy), investment growth (di), hours (h), inflation (π), and credit spread (cs) match almost perfectly with the empirical counterparts. For the growth of relative price of consumption to investment goods (μ_ψ), risk-free rate (r), and the credit growth (db), the model is able to match the general trend but has difficulty in matching the magnitude of the large peaks and troughs. A similar conclusion can be drawn from Panel A of Table 3, which reports the summary statistics of the model-implied variables and their observed counterpart. The standard deviations of model-implied μ_ψ, r, and db are smaller than the standard deviations in the data, while the volatility of other variables are comparable with the values in the data.

Another noticeable difference between the model-implied and observed variables is that the mean growth rate of credit supply (db) and the credit spread (cs) are much larger in the data than in the model, being 0.73% vs. 0.35% and 1.95% vs. 0.41%. As explained in the Online Appendix, when we construct the data, we follow CMR and detrend all the variables. The reason is that the model is stationary on a balanced growth path and all the economic variables are growing at the same rate. This common growth rate is calibrated based on the average GDP growth (μ_z) and growth rate of relative price of consumption to investment goods (μ_ψ). If macroeconomic variables do not grow at the same rate in our sample, the model is not able to explain the differences in trend. Therefore, by detrending the variables used in the estimation, we ask the model to match the fluctuations from the mean and ignore the differences in trend. In the data, credit supply happens to grow much faster in our sample period, and the model is not able to capture that phenomenon. One way to capture the higher growth rate of credit supply is to create a credit supply specific shock and give this shock a positive trend. For our purpose of extracting fundamental shocks, the fluctuations of macroeconomic variables along the business cycles are more important than the constant trend. We choose to adopt the simplest possible model to achieve that purpose. As for the large difference in the model-implied and observed credit spreads, it might be partially due to the mismatch that the observed credit spread is computed from interest rates on public bonds, while in the model, it is the average borrowing cost of all firms, private or public.

Panel A of Table 3 also reports the correlation and its p-value of each pair of model-implied variable and its observed variables. All pairs are significantly positively correlated, with p-value close to zero. And most of the correlations are higher than 70%. Overall, the model-implied variables match the data very well, especially given that we use only four latent shocks to match nine macroeconomic variables.

3.3 Return on Capital

In this subsection, we compare the return on capital in the model with the return on the market portfolio in the data.[7] As defined in equation (9), return on capital R_k is the nominal return on raw capital. Its value depends on the marginal productivity of capital in the intermediate goods sector and the change in price of raw capital, the latter of which is determined by the marginal adjustment costs of investments. The return on capital in our model is analogous to the investment return in the q-theory models of, for example, Liu, Whited, and Zhang (2009).

We compute the time series of model return on capital based on the estimated shocks and the posterior modes of the parameters. The level of the two series are close, with the mean of return on capital being 1.57% and the mean of market return being 1.61% at quarterly frequency. The market return is four times more volatile than the return on capital, with standard deviations

[7] In our model, firms in the final and intermediate goods production sectors earn zero profits and do not own capital. Therefore, those firms have zero market value and does not have properly defined returns on firm asset.

of 8.44% and 1.93%, respectively. The reason that the model can generate such a high return on capital is the fact that the effective risk aversion is high due to the presence of habit formation. It is not surprising that the model return is less volatile than the market return given that only macroeconomic data is used in the estimation of the model and those variables generally have much lower volatility than stock return does. It is worthwhile pointing out that unlike most of the asset pricing papers, which usually calibrate the parameters to match the Sharpe ratio of the market, no return data is used in our estimation.

In addition, the model return on capital and return on market portfolio in the data share similar dynamics. The correlation of these two series is 23% with p-value close to zero, as shown in Panel B of Table 3. Because return data plays no role in the estimation of the model, such a high correlation between the two return measures lend support to our model and the estimation.

3.4 Price of Risk

In this subsection, we investigate the signs of these four shocks' risk premia under the posterior modes of the estimated parameters. Section 2.6 shows that the sign of the risk premium of shock e depends on the correlation between the shock and the pricing kernel, ρ_{em}. A positive correlation indicates negative risk premium and vice versa.

The Online Appendix shows that the pricing kernel can be written in terms of the shock to the habit-adjusted consumption growth, ε^{ch}, and the shock to the wealth-consumption ratio, ε^{wc}:

$$m_{t,t+1} = \mathbb{E}_t[m_{t,t+1}] - \gamma\varepsilon^{ch}_{t+1} - \frac{\gamma-\psi}{1-\psi}\varepsilon^{wc}_{t+1} \tag{16}$$

where

$$\begin{aligned}
\varepsilon^{ch}_{t+1} &\equiv \Delta c_{h,t+1} - \mathbb{E}_t[\Delta c_{h,t+1}] \\
\varepsilon^{wc}_{t+1} &\equiv wc_{t+1} - \mathbb{E}_t[wc_{t+1}] = (\mathbb{E}_{t+1} - \mathbb{E}_t)\sum_{j=1}^{\infty}\kappa_1^j[\Delta\tilde{d}_{a,t+1} + (1-\psi)\Delta c_{h,t+1})\,.
\end{aligned}$$

Here, $\tilde{d}_{a,t} = \ln(D_{a,t}/C_{h,t})$ and $D_{a,t}$ is the payout of the wealth portfolio given by $D_{a,t} = C_{h,t} - \kappa W_t L_t / P_t$. Both κ and $0 < \kappa_1 < 1$ are constants defined in the Online Appendix. Here we use lowercase letters to represent the natural logarithm of their uppercase counterparts.

Under our estimation, inverse of EIS (ψ) is 0.82 and risk aversion (γ) is 5.23. Thus, the pricing kernel negatively depends on the shock to habit-adjusted consumption growth and the shock to wealth-consumption ratio. The definitions of ε^{ch} and ε^{wc} indicate that an increase in consumption leads to a positive shock to the habit-adjusted consumption growth, ε^{ch}, and a positive shock to the wealth-consumption ratio, ε^{wc}. However, an increase in labor supply leads to negative ε^{wc} since it decreases the payout of the wealth portfolio. The correlation between the pricing kernel and the shock will depend on how the shocks affect consumption and labor, and the relative magnitude of these effects.

Row (1) of Figure 2 plots the impulse responses of m, ε^{ch}, ε^{wc}, and labor supply l to a positive NT shock. After a positive NT shock, both consumption and labor supply go up due to higher productivity. Higher consumption leads to a positive ε^{ch} while higher labor supply leads to a negative ε^{wc}. Under the estimated values of parameters, the latter dominates the former and the pricing kernel drops after a positive NT shock ($\rho_{zm} < 0$), indicating a positive risk premium.

Row (2) of Figure 2 plots the impulse responses of m, ε^{ch}, ε^{wc}, and labor supply l to a positive IST shock. A lower price of investment goods means that a smaller amount of output can produce more capital and a larger fraction of output can be consumed. Moreover, expecting higher output in the future due to increased capital, household increase consumption today due to consumption smoothing incentives, resulting in a positive ε^{ch}. However, higher capital level leads to higher marginal labor productivity. Consequently, labor supply also increases, which leads to a negative ε^{wc}. The decrease in wealth-consumption ratio dominates the increase in consumption, and the pricing kernel goes up ($\rho_{\psi m} > 0$). Therefore, the risk premium of IST shock in our estimated model is negative.

Note that even though our model implies a negative risk premium for IST shock as Papanikolaou (2011) do, the underlying mechanism is different. In Papanikolaou (2011), IST risk premium is negative because a positive IST shock induces a drop in consumption, hence increasing marginal utility and the pricing kernel. Consistent with our finding, Garlappi and Song (2016b) show that in a model with flexible capital utilization as ours, consumption can go up after a positive IST shock.[8] Garlappi and Song (2016b) finds that under their calibrated values of parameters, the pricing kernel drops, implying a positive IST risk premium. On the contrary, under our estimated values of parameters, the effect of wealth-consumption ratio dominates the effect of consumption growth and the pricing kernel increases after a positive IST shock.

Row (3) of Figure 2 plots the impulse responses of m, ε^{ch}, ε^{wc}, and labor supply l to a positive MP shock. After a contractionary MP shock, interest rate goes up and cools down the economy. Both consumption and labor supply drop, resulting in a negative ε^{ch} and a positive ε^{wc}. The former dominates the latter and the pricing kernel goes up ($\rho_{rm} > 0$), indicating a negative risk premium for the MP shock.

Row (4) of Figure 2 plots the impulse responses of m, ε^{ch}, ε^{wc}, and labor supply l to a positive risk shock. With a rise in risk shock, the probability of a low ω increases and bank raises the interest rate on loans to entrepreneurs to cover bankruptcy costs. Entrepreneurs respond by borrowing less and produce less capital, leading to lower consumption. Due to the existence of habit, household has strong incentive to increase labor supply to reduce the reduction in consumption. Consequently, both ε^{ch} and ε^{wc} are negative and the pricing kernel goes up ($\rho_{om} > 0$), indicating a negative risk premium for the risk shock.

In sum, the risk premia of the NT, IST, MP and risk shocks are positive, negative, negative, and negative, respectively, in the model with the values of parameter presented in Tables 1 and 2.

3.5 Inspecting the Mechanisms

NT shock is the most studied fundamental shock and is the embedded technology shock in the Cobb-Douglas production function. A positive NT shock increases the productivity of both capital and labor. IST shock is an investment specific technology shock. A positive IST shock lowers the price of investment goods, and the price of capital because of lower replacement costs. This in turn makes growth options more valuable due to lower installment costs but assets-in-place (AIP) less valuable due to lower price of capital.[9] MP shock is the unexpected shock in the

[8] We indeed find that consumption and IST shock is positively correlated in the data, consistent with the evidence in Garlappi and Song (2016a).

[9] Greenwood and Jovanovic (1999) show that the stock-market incumbents at 1968 lost 75% of their market value in the next 5-6 years because the old technology embodied in their capital became obsolete in the emergence of information technology. On the contrary, new entrants to the stock market adopted the new technology and experienced a drastic

Taylor rule. A positive MP shock leads to unexpected increase in nominal interest rate, which generally leads to higher real interest rate under a stable Taylor rule, i.e., $\Phi_\pi > 1$. Thus, a positive MP shock leads to contraction of the economy.

Risk shock is first introduced in Bernanke, Gertler, and Gilchrist (1999) and we follow CMR to incorporate it in a DSGE model. In the presence of risk shock, credit market frictions play a quantitatively important role in shaping business cycle dynamics. Entrepreneurs combine their own wealth with bank loans to acquire raw capital and transform it into effective capital, which is rented by intermediate goods producers. There is idiosyncratic uncertainty in the efficacy of this transformation by each entrepreneur and this uncertainty exhibits a cross-sectional dispersion. We refer to the change in the magnitude of this dispersion as risk shock. When an entrepreneur's efficacy is too low, he defaults on his bank loan and bankruptcy costs are incurred due to asymmetric information and costly monitoring (Townsend, 1979). A positive Risk shock leads to a larger dispersion in the efficacy of transforming raw capital into effective capital, which in turn leads to more defaults. In equilibrium, banks require higher credit spread on loans and total credit extended to entrepreneurs drops. With fewer financial resources, entrepreneurs acquire less raw capital, as a result, investment, output, and consumption all fall. Note that although both MP and Risk affect firm's financing costs, a positive MP shock raises such costs by imposing a higher risk-free rate, while a positive Risk shock raises the credit spread between interest rates on risky and risk-free assets.

Because of the aforementioned reasons, firm value increases after a positive NT shock because of higher productivity, indicating a positive exposure to NT shock. A positive IST shock leads to lower value of AIP and higher value of growth options. The change in total firm value depends on which effect dominates, AIP or growth options. A positive MP shock leads to contraction of economic activity and generally lower firm value, implying negative MP exposures. For the same reason, we also expect negative Risk shock exposure from firms. Next, we explore possible channels through which those four fundamental shocks may explain the well-known size, value, and investment premia, which are the focus of our empirical exercises.

Size premium — Small firms are likely to be more positively exposed to NT shocks and more

surge in their market value.

negatively exposed to IST, MP, and Risk shocks. First, due to fixed operating costs, small firms on average have higher operating leverage, and are more sensitive to the changes in productivity. This implies that small firms have more positive exposure to NT shock. Second, results in Panel A of Table 6 show that the effect of IST shock on AIP dominates that on growth options and size portfolios on average have negative exposure to IST shock. Small firms have higher Book-to-Market (BM) ratio (Novy-Marx, 2013) and AIP constitutes a larger fraction of their firm value. Consequently, the value of small firms drops more after a positive IST shock, indicating a more negative IST exposure. Third, size is commonly used as a measure of financial constraints. The literature has shown that small firms on average have larger financing costs and more likely to be rationed in the credit market. Thus these firms are likely to be more sensitive to changes in interest rates and credit market conditions, i.e., more negatively exposed to MP and Risk shocks.

In sum, under the assumption that NT shock carries positive risk premium, and IST, MP, and Risk shocks carry negative risk premia, the differences in risk exposure to these four shocks between small and large firms all contribute positively to the size premium.

Value premium — Value firms are likely to be more positively exposed to NT shocks and more negatively exposed to IST, MP, and Risk shocks. First, value firms are burdened with more unproductive capital during recessions when risk premium is high and their value drops more after a negative NT shock (Zhang, 2005), indicating a more positive NT exposure. Second, by construction, AIP constitutes a larger fraction of firm value for value firms than for growth firms. After a positive IST shock, value firms experience larger drop in value, indicating a more negatively IST exposure. Third, value firms are also more financially levered due to higher value of tangible assets. As a result, they are more negatively affected by MP and Risk shocks and have more negative exposures to them.

In sum, under the assumption that NT shock carries positive risk premium, and IST, MP, and Risk shocks carry negative risk premia, the differences in risk exposure to these four shocks between value and growth firms all contribute positively to the value premium.

Investment premium — Firms with higher investment-to-capital (IC) ratio are likely to be more positively exposed to NT shocks and more negatively exposed to IST, MP, and Risk shocks. First, a positive NT shock increases the values of both AIP and growth options, and the value of growth options goes up more because growth options are levered claims. Firms with higher IC ratio have larger fraction of value coming from growth options and thus more positively react to NT shock. Note that the exposure to NT shock contributes negatively to investment premium because NT shock carries positive risk premium. Second, a positive IST shock makes AIP less valuable and growth options more valuable. Panel A of Table A6 in the Online Appendix shows that the IST exposure of investment portfolios is negative, implying that the value decrease in AIP dominates the value increase in growth options. Firms with higher IC ratio derive a larger fraction of firm value from growth options and is less negatively exposed to IST shock. Third, firms with higher IC ratio on average have larger external financing needs and naturally are more sensitive to the financial market conditions. We expect those firms to be more negatively exposed to MP and IST shocks.

In sum, under the assumption that NT shock carries positive risk premium, and IST, MP, and Risk shocks carry negative risk premia, the differences in risk exposure to IST, MP, and Risk shocks between high and low IC firms contribute positively to the investment premium, while the difference in risk exposure to NT shock contributes negatively. Next, we examine how well the model-implied fundamental shocks explain the cross section of stock returns empirically.

4 Empirical Asset Pricing Analysis

The close match between the nine model-implied macroeconomic variables and their observed counterparts suggests that the extracted four shocks capture the salient features of the economy. In this section, we investigate the asset pricing implications of the estimated DSGE model. In particular, we examine whether the latent shocks implied by the DSGE model can explain the cross-sectional returns of a wide range of financial assets.

4.1 Correlation Between Model-implied Shocks, Return Factors, and Empirical Measures of the IST Shock

In order to facilitate comparison, we normalize the four model-implied shocks to zero mean and unit variance. Table 4 reports the correlations between the four model-implied shocks, six return factors, and three empirical measures of the IST shock widely used in the literature (Garlappi and Song, 2016a; Kogan and Papanikolaou, 2013, 2014).[10] Our sample period covers from the second quarter in 1957 to the fourth quarter in 2015.[11]

Panel A presents the correlation matrix of the four model-implied shocks. Except for the IST shock, none of the other three shocks have significant correlation with each other. The IST shock is significantly and negatively correlated with the other three shocks. Its correlations with the NT, MP, and Risk shocks are -0.353, -0.259, -0.147, respectively, which are all significant at the 5% level.

Panel B presents the correlation between the four model-implied shocks, six return factors, and three measures of IST shocks. The six return factors are the Fama-French five factors and the momentum factor (MOM). The Fama-French five factors include the market excess return (MKT), small minus big (SMB), high minus low (HML), robust minus weak (RMW), and conservative minus aggressive (CMA) portfolio returns. The three measures of the IST shock are (the negative of) the change in the relative price of investment goods (Ishock), the return difference between investment and consumption goods sectors (IMC), and the growth rate difference between aggregate investment and consumption (gIMC).

The NT shock is positively correlated with the MKT factor (correlation = 0.200 and p-value = 0.004) and negatively correlated with the CMA (correlation = -0.146 and p-value = 0.035) and MOM (correlation = -0.186 and p-value = 0.004) factors.

The IST shock is negatively correlated with the MKT factor (correlation = -0.116 and p-value = 0.094) and does not have significant correlation with any other return factors. The negative correlation between the IST shock (especially for the measures of Ishock and gIMC) and the stock market return during the 1948-2012 period is also noted by Garlappi and Song (2016a).

[10]We sincerely thank Zhongzhi Song for kindly sharing his data on the empirical measures of the IST shock with us.

[11]Results involving accounting variables such as investment and profitability are based on the sample starting from the third quarter in 1963 due to data availability.

Among the three measures of IST shocks widely used in the literature, our model-implied IST shock is most closely related to the Ishock measure with a correlation of 0.203 (p-value = 0.002). One potential reason is that the change in the relative price of investment goods is one of the nine macroeconomic variables used in our estimation.

The MP shock is negatively correlated with the SMB factor (correlation = -0.158 and p-value = 0.022) but insignificantly correlated with all other return factors. The Risk factor does not have significant correlation with any of the return factors.

4.2 Risk Premia of Model-Implied shocks

We estimate the risk premia associated with the four model-implied shocks using the two-step Fama and MacBeth (1973) cross-sectional regression methodology. The test assets used to estimate the risk premia are portfolios that display a wide spread in average returns. We first choose the most widely used 30 portfolios in the literature, including ten size, ten book-to-market, and ten momentum portfolios (Bansal, Dittmar, and Lundblad, 2005; Cooper and Priestley, 2011; Liu and Zhang, 2008). To have an economically meaningful and statistically powerful test on asset pricing models, Lowellen, Nagel, and Shanken (2010) and Daniel and Titman (2012) recommend to expand test assets beyond characteristics-based portfolios, such as to include industry portfolios. Lowellen, Nagel, and Shanken (2010) argue that "the additional portfolios do not need to offer a big spread in expected returns; the goal is simply to relax the tight factor structure of size-B/M portfolios". Therefore, we include ten industry portfolios in addition to the 30 characteristics-based portfolios.[12]

Our first set of test assets thus includes the following value-weighted portfolios: ten size, ten book-to-market, ten momentum, and ten industry portfolios. Recent studies in Hou, Xue, and Zhang (2015) and Fama and French (2015) suggest that investment and profitability are important characteristics that generate large cross-sectional return spreads. We thus use a second set of test assets as a robustness check, which include ten size, ten book-to-market, ten momentum, ten investment, ten profitability, and ten industry portfolios.

Following Fama and French (1992), Lettau and Ludvigson (2001), and Liu and Zhang (2008),

[12] We construct the quarterly return series of test assets from the monthly portfolio returns downloaded from Ken French's website.

we use the full sample to estimate factor loadings of the test assets in the first stage regression.[13] The same test assets are used in the second-stage cross-sectional regressions to estimate the risk premia of the model-implied factors. We adjust the estimation errors in betas following Shanken (1992) and autocorrelation and heteroscedasticity following Newey and West (1987).

Panel A of Table 5 reports the risk premia of four model-implied shocks estimated based on the first set of test assets (ten size, ten book-to-market, ten momentum, and ten industry portfolios). Rows 1-4 report the risk premia estimated from a univariate model for each shock. Row 5 reports the risk premia estimated from a four-factor multivariate model.

The risk premium estimate for the NT shock is positive and significant in the univariate model, which is 1.69% per year with a t-statistic of 6.53. in the the multivariate model, the risk premium of the NT shock remains positive but becomes insignificant.

The risk premium estimates for IST, MP, and Risk shocks are all negative and significant in the univariate model, which are -3.95% (t-statistic = -6.73), -2.20% (t-statistic = -6.95), and -3.88% (t-statistic = -6.78), respectively. In the multivariate model, the risk premia of IST and Risk shocks remain significantly negative, while the risk premium of the MP shock becomes insignificant.

The results are similar when we estimate the risk premia using the second set of test assets, which includes ten size, ten book-to-market, ten momentum, ten investment, ten profitability, and ten industry portfolios. The results are reported in Panel B of Table 5. The risk premium is significantly positive for the NT shock and significantly negative for IST, MP, and Risk shocks in the univariate model. In the multivariate model, the risk premia remain negative and significant for the IST and Risk shocks, but become insignificant for the NT and MP shocks.

Taken together, based on the two-step Fama and MacBeth (1973) cross-sectional regression, the NT shock is estimated to have a positive premium and the IST, MP, and Risk shock bears negative premia in univariate models. These results are consistent with our model predictions on the signs of these shocks in Section 3.4. In the four-factor multivariate model, the risk premia of IST and Risk shocks remain negative and significant, while the risk premia of NT and MP shocks become insignificant. This result suggests that in the horse race among the four shocks,

[13]Because our data is in quarterly frequency, the estimates based on rolling regressions and extending windows are too noisy.

IST and Risk shocks play a more important role during our sample period.

4.3 Portfolio Returns and Factor Loadings on Model-Implied Shocks

To study the effect of model-implied shocks on cross-sectional asset returns, we need to know both the risk premia of shocks and factor loadings of an asset return with respect to the factors. In the previous section, we estimate risk premia of model-implied shocks via the two-step Fama and MacBeth (1973) regression. In this subsection, we estimate the factor loadings of several prominent characteristics-based test asset returns, such as the size and book-to-market decile portfolios, with respect to the four model implied shocks.[14]

Panel A of Table 6 reports the returns and estimated betas of ten size-sorted portfolios for the quarterly sample during 1957q2-2015q4. The quarterly portfolio return decreases from 3.70% in the smallest decile to 2.62% in the biggest decile, which implies a small-minus-big return spread of 1.09 with a t-statistic of 1.76. The factor loadings are obtained from time-series regressions of portfolio excess returns on the four model-implied shocks, including the NT, IST, MP, and Risk shocks. The results suggest that small firms load more on the NT shocks and load less on the IST, MP, and Risk shocks. As evident from our previous estimates of risk premia, NT shock bears a positive risk premium and IST, MP, and Risk shocks bear negative risk premia. The positive loadings on the NT shock and the negative loadings on the IST, MP, and Risk shocks indicate that the exposure to these four shocks contribute positively to the return spread between small and big firms.

Panel B of Table 6 reports the returns and estimated betas of ten book-to-market sorted portfolios. The quarterly portfolio return increases from 2.63% in the lowest decile to 3.99% in the highest decile, which implies a high-minus-low return spread of 1.36 with a t-statistic of 2.21. The loadings of ten book-to-market sorted portfolios on IST, MP, and Risk shocks are all negative. The results on factor loadings across portfolios suggest that high book-to-market firms load less on all four shocks than low book-to-market firms. Thus the exposure to IST, MP, and Risk shocks contributes positively to the high-minus-low return spread, while the exposure to NT shock contributes negatively.

[14] To conserve space, we put the beta estimates of other test assets, including the investment, profitability (earnings), momentum, and long-term reversal portfolios, in the Online Appendix.

It is worth noting that betas of portfolios returns estimated with respect to macroeconomic variables are in general less significant than those estimated with respect to return-based factors, such as mimicking portfolios. For example, as discussed by Cochrane (2005) and Cooper and Priestley (2011), factors in the return space generally provide sharper beta estimates although the magnitude of the beta estimates are similar.

4.4 Expected Cross-Sectional Return Spreads

The above estimates of risk premia and the estimates of factor loadings enable us to compute the fraction of cross-sectional return spreads that are explained by model-implied shocks. We consider six widely studied cross-sectional return spreads, namely, the small-minus-big size spread, the high-minus-low value premium, the low-minus-high investment spread, the high-minus-low earnings spread, the high-minus-low momentum spread, and the low-minus-high long-term reversal spread.[15]

We choose these six cross-sectional return spreads for a number of reasons. First, the recent study by Hou, Xue, and Zhang (2015) suggests that a four-factor q-theory model with market, size, investment, and profitability factors can explain a large number of cross sectional return spreads. Fama and French (2015) find similar results for a five-factor model with market, size, book-to-market, investment, and profitability factors.[16] Second, we include momentum due to its popularity in factor models such as the four-factor Carhart (1997) model. We further include the long-term reversal return spread since it captures the long-horizon price effect while momentum captures relative short-horizon price effect.

In Panel A of Table 7, we present the average cross-sectional return spreads (R), the t-statistics of R (t(R)), the expected cross-sectional return spreads (ER), the ratio of ER/R, the difference between R and ER (effectively the alpha of the model), and t-statistics of the difference (t(diff)). The expected risk premium due to the exposure to a risk factor is calculated as the risk exposure times the risk premium of the corresponding risk factor ($\beta_i \lambda_i$). The risk exposures are estimated from

[15] All the portfolios used in this paper, including the size, book-to-market, investment, operating profitability, earnings, momentum, long-term reversal, and industry portfolios, are taken from Ken French's web site. We construct the quarterly return series of test assets from the monthly portfolio returns.

[16] In our sample period, portfolios sorted by operating profitability does not have a significant return spread. We thus replace operating profitability portfolios with earnings portfolios.

the full sample from 1957q2 and 2015q4. The risk premia of risk factors are estimated using the multivariate model as Panel A in Table 5. ER is calculated as the summation of the expected risk premia from all four model-implied shocks, $ER = \sum_i \beta_i \lambda_i,\ i = NT,\ IST,\ MP,\ and\ Risk.$ Panel B of Table 7 presents the expected risk premium due to the exposure to each shock, respectively. The t-statistics are adjusted for autocorrelation and heteroscedasticity following Newey and West (1987).

The small-minus-big size spread is the difference in average return between the small and big size decile portfolios. Over the period 1957q2-2015q4, the quarterly small-minus-big size spread is 1.09% with a t-statistic of 1.76. The expected size spread calculated from the four-shock model is 1.82% per quarter, which explains 167.6% of the actual size spread. The difference between the actual and expected size spreads is -0.73%, which is insignificant with a t-statistic of 1.19. The result suggests that we cannot reject the hypothesis that the four-factor model explains the size spread at the 5% significance level.

The value premium is the difference in average return between the high and low book-to-market decile portfolios. Over the period 1957q2-2015q4, the quarterly value premium is 1.36% with a t-statistic of 2.21. The expected value premium calculated from the four-shock model is 1.22% per quarter, which explains 89.5% of the actual value premium. The difference between the actual and expected value premia is 0.14%, which is insignificant with a t-statistic of 0.23.

The investment spread is the difference in average return between the low and high investment decile portfolios. Over the period 1963q3-2015q4, the quarterly investment spread is 1.35% with a t-statistic of 3.05. The expected investment spread calculated from the four-shock model is 0.71% per quarter, which explains 52.6% of the actual investment spread. The difference between the actual and expected investment spreads is 0.64%, which is insignificant with a t-statistic of 1.45.

The earnings spread is the difference in average return between the high and low earnings decile portfolios. Over the period 1963q3-2015q4, the quarterly earnings spread is 1.28% with a t-statistic of 2.40. The expected earnings spread calculated from the four-shock model is 0.88% per quarter, which explains 68.8% of the actual earnings spread. The difference between the actual and expected earnings spreads is 0.40%, which is insignificant with a t-statistic of 0.75.

The momentum spread is the difference in average return between the high and low momentum decile portfolios. Over the period 1957q2-2015q4, the quarterly momentum spread is 3.94% with a t-statistic of 4.97. The expected momentum spread calculated from the four-shock model is 0.54% per quarter, which explains 13.8% of the actual momentum spread. The difference between the actual and expected momentum spreads is 3.39%, which is significantly positive with a t-statistic of 4.29. The result suggests that we reject the hypothesis that the four-factor model explains the momentum spread at the 5% significance level.

The long-term reversal spread is the difference in average return between the low and high long-term reversal decile portfolios. Over the period 1957q2-2015q4, the quarterly long-term reversal spread is 1.13% with a t-statistic of 1.75. The expected long-term reversal spread calculated from the four-shock model is 1.00% per quarter, which explains 88.5% of the actual long-term reversal spread. The difference between the actual and expected long-term reversal spreads is 0.13%, which is insignificant with a t-statistic of 0.20.

In Panel A of Table 7, we also present the CAPM alpha (α), the Fama-French three-factor alpha (α_{ff3}), the Fama-French five-factor alpha (α_{ff5}), and the Hou, Xue, and Zhang (2015) q-theory alpha (α_q). Except for the size spread, the CAPM alphas are significant for all cross-sectional return spreads. The Fama-French three factor model performs better than the CAPM model, leaving only the book-to-market, investment, and momentum spreads unexplained. The Fama-French five factor model further improves by leaving only the momentum alpha significant. The q-theory model outperforms the Fama-French five factor model in capturing the momentum effect, the alpha of which is reduced to 2.03% with a t-statistic of 1.54.

The above four return-based factor models provide a benchmark for us to evaluate how our model performs in explaining the cross section of returns. In terms of the significance and absolute magnitude of alphas, our model is closest to the Fama-French five factor model. Only the momentum alpha is significant for both models. Our model has larger absolute magnitude of size, investment, and earnings alphas but smaller book-to-market, momentum, and long-term reversal alphas than the Fama-French five factor model. Given the well-known and long-standing difficulty for macroeconomic factors to compete with return-based factors in explaining the cross-sectional asset returns, we have made an encouraging step in the direction that links the real side of the economy to the capital market more closely.

Panel B of Table 7 decomposes the expected return spreads of the six cross sections into individual components due to risk exposure to individual model-implied shock. The results suggest that the IST and Risk shocks explain substantial amount of the cross-sectional return spreads, while the NT and MP shocks have very limited explanatory power. For example, the IST shock explains 47.8% of the size spread, 73.0% of the value premium, 57.1% of the investment spread, 41.4% of the earnings spread, 28.7% of the long-term reversal spread, and 29.7% of the momentum spread. The Risk shock explains 132.4% of the size spread, 42.3% of the value premium, 45.8% of the earnings spread, and 63.5% of the long-term reversal spread. The Risk shock has very little explanatory power for the investment and momentum spread. While the NT shock can explain 15.3% of the size premium, it cannot explain any of the rest cross-sectional spreads. The explanatory power of the MP shock is negligible for all return spreads.

Taken together, the four-factor model explains a sizable proportion of the size, book-to-market, investment, earnings, and long-term reversal return spread but cannot fully explain the momentum spread. Among the four model-implied shocks, the IST and Risk shock have the strongest explanatory power for most of the six cross-sectional return spreads, while the NT and MP shocks play less important roles.

5 Robustness

5.1 Risk Premium of Model-Implied Shocks: Alternative Test Assets

We assess the robustness of our risk premium estimates by using alternative test assets. The first set includes only size and book-to-market decile together with ten industry portfolios. The second set expands the choice of test assets to decile portfolios along four different characteristics, including size, book-to-market, investment, and profitability, together with ten industry portfolios. We drop the momentum portfolio in order to evaluate its effect on our results. The results are reported in Panels A and B of Table A1, respectively.

The risk premia estimated based on the two alternative sets of test assets are qualitatively similar with our previous estimates. In univariate models, the NT shock carries a positive risk premium, wile the IST, MP, and Risk shocks carry negative risk premia. The magnitude of the risk premia are also similar across different test assets.: $\sim 2\%$ for the NT shock, $\sim -4\%$ for the IST shock, $\sim 2\%$ for the MP shock, $\sim 4\%$ for the Risk shock.

In the four-factor multivariate model, the risk premia of the IST and Risk shocks remain negative and significant. The risk premium of the NT shock becomes smaller in magnitude but remains significant. The risk premium of the MP shock becomes insignificant.

In sum, the risk premia of our model-implied shocks are robust across different test assets. The estimates of risk premia are less sensitive to the inclusion of momentum portfolios than previous studies (Garlappi and Song (2016a)) suggest. The difference may lie in the fact that previous studies measure the IST shock using empirical proxies, while we extract the IST shock using full-information Bayesian estimation. This result suggests that the DSGE structure imposed in our estimation helps to filter out noises.

5.2 Risk Premium of Model-Implied Shocks: Subperiod Analysis

In order to further assess how our risk premium estimates vary over time, we split our sample into two subperiods: the pre-1990 subperiod from 1957q2 to 1989q4 and the post-1990 subperiod from 1990q1 to 2015q4. We estimate the risk premia of the four model-implied shocks for the two subperiods and report the results in Panels A and B of Table A2 in the Online Appendix, respectively.

In univariate models, the risk premium estimates, in general, have smaller magnitude and weaker statistical significance in the post-1990 subperiod than the pre-1990 subperiod. In the four-factor multivariate models, the relative importance of different shocks also changes over time. The risk premium of the NT shock is 0.77% (t-statistic = 3.19) in the pre-1990 period, but flips sign and becomes -0.82 (t-statistic = -3.86) in the post-1990 period. The risk premium of the IST shock is significantly negative at -2.44% (t-statistic = -7.95) in the pre-1990 period but becomes insignificant in the post-1990 period, which is consistent with the finding in Garlappi and Song (2016a) that the risk premium of IST shock is stronger in early times and becomes weaker in recent years. The risk premium of the MP shock is insignificant in the pre-1990 period but becomes significantly negative at -0.81% (t-statistic = -3.27) in the post-1990 period, which echoes the recent discussion on the increasing importance of monetary policy, especially during the financial crisis. The risk premium of the Risk shock is relatively stable.

In sum, the signs and significance of the risk premia of the four shocks in univariate regressions are stable across the two subperiods, but are generally not stable in multivariate regressions. The only shock with stable and significant risk premium in both univariate and multivariate regressions is the Risk shock.

5.3 Principal Component Analysis

To evaluate the importance of the DSGE model to the estimation of fundamental shocks, we implement a nonstructural estimation of shocks based on the same nine macroeconomic variables. We perform a principal component analysis on the these variables and extract four principal components with eigenvalue larger than one. Asset pricing tests show that a four-factor model using these principal components can only explain the size spread, but not the book-to-market, investment, earnings, and long-run reversal spreads. Therefore, the asset pricing performance of those principal components is much worse than the performance of our model implied four shocks. This result indicates that the DSGE model does impose a useful structural constraint on the estimation of fundamental shocks. To conserve space, we include those results in the Online Appendix.

6 Conclusion

In this paper, we estimation of a DSGE model based on nine macroeconomic variables and extract the time-series of four latent fundamental shocks. Asset pricing tests show that our model-implied four-factor model can explain a number of prominent cross-sectional return spreads: size, book-to-market, investment, earnings, and long-term reversal, although the model can not explain the momentum spread. Among the four shocks, the IST shock and Risk shock play the most important role in explaining those return spreads. Overall, our results highlight the great potential of integrating macroeconomic dynamics and asset prices into the unified general equilibrium framework of DSGE models.

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Figure 1: **Observed and Model-Implied Macroeconomic Variables**

This figure shows the observed (in red) and model implied (in black) time series of consumption growth (dc), output growth (dy), investment growth (di), wage growth (dw), (normalized) hours (h), 3-month T-bill rate (r), negative of growth rate of investment price (μ_ψ), and inflation (π), growth of credit supply (db), and difference between the interest rates on BAA-rated corporate bonds and the 3-month T-bill rate (Z) for the sample period 1957Q2 - 2015Q4. All variables are demeaned and all growth rate are in logarithm.

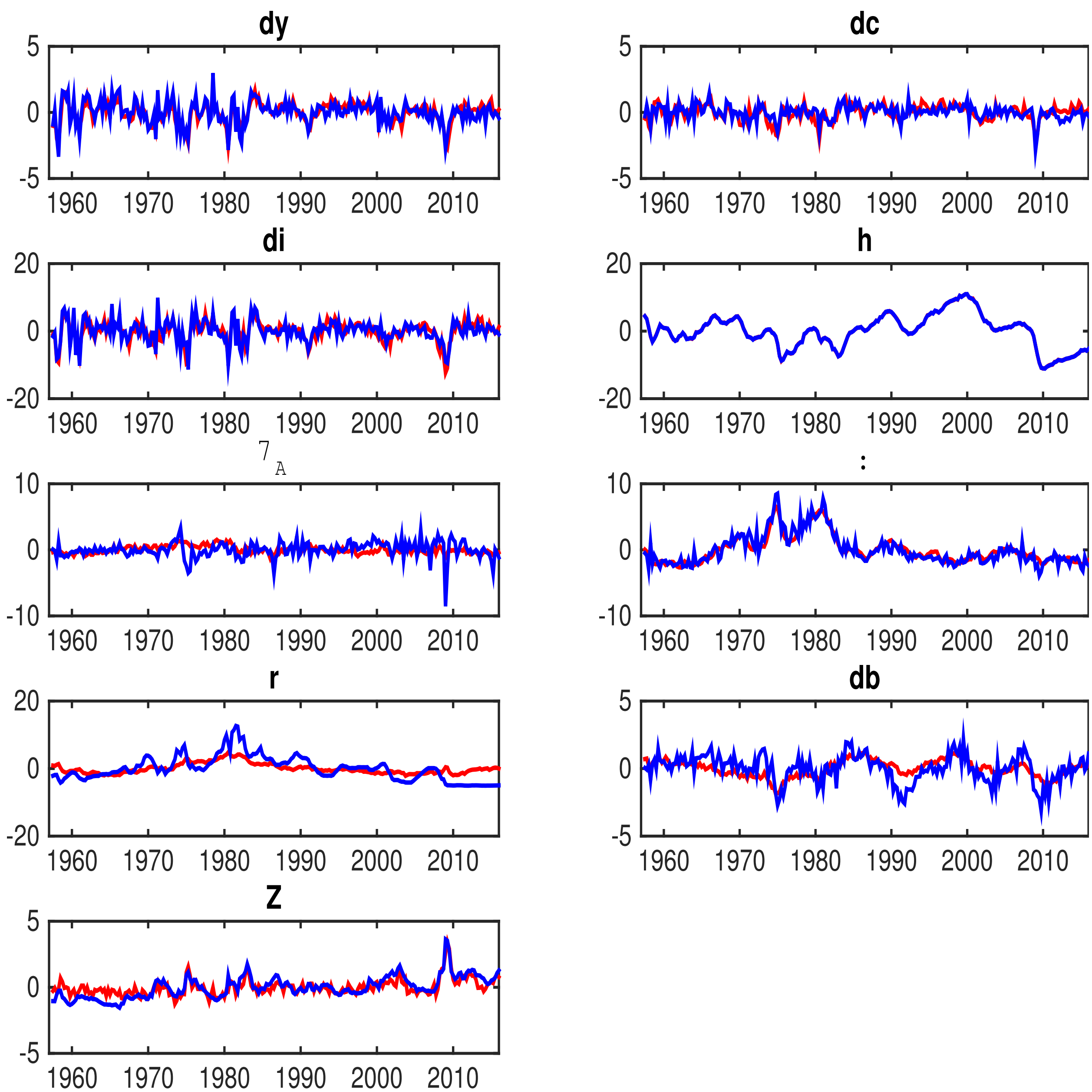

Figure 2: **Impulse Responses**

This figure present the impulse responses of the stochastic discount factor (m), shock to habit-adjusted consumption growth (ε_{ch}), shock to wealth-consumption ratio (ε_{wc}), and labor (l) in columns 1-4, respectively. The figures in rows (1)-(4) plots the responses of these three variables with respect to one standard deviation increase in the NT, IST, MP, and risk shocks, respectively. All three variables are in logarithm.

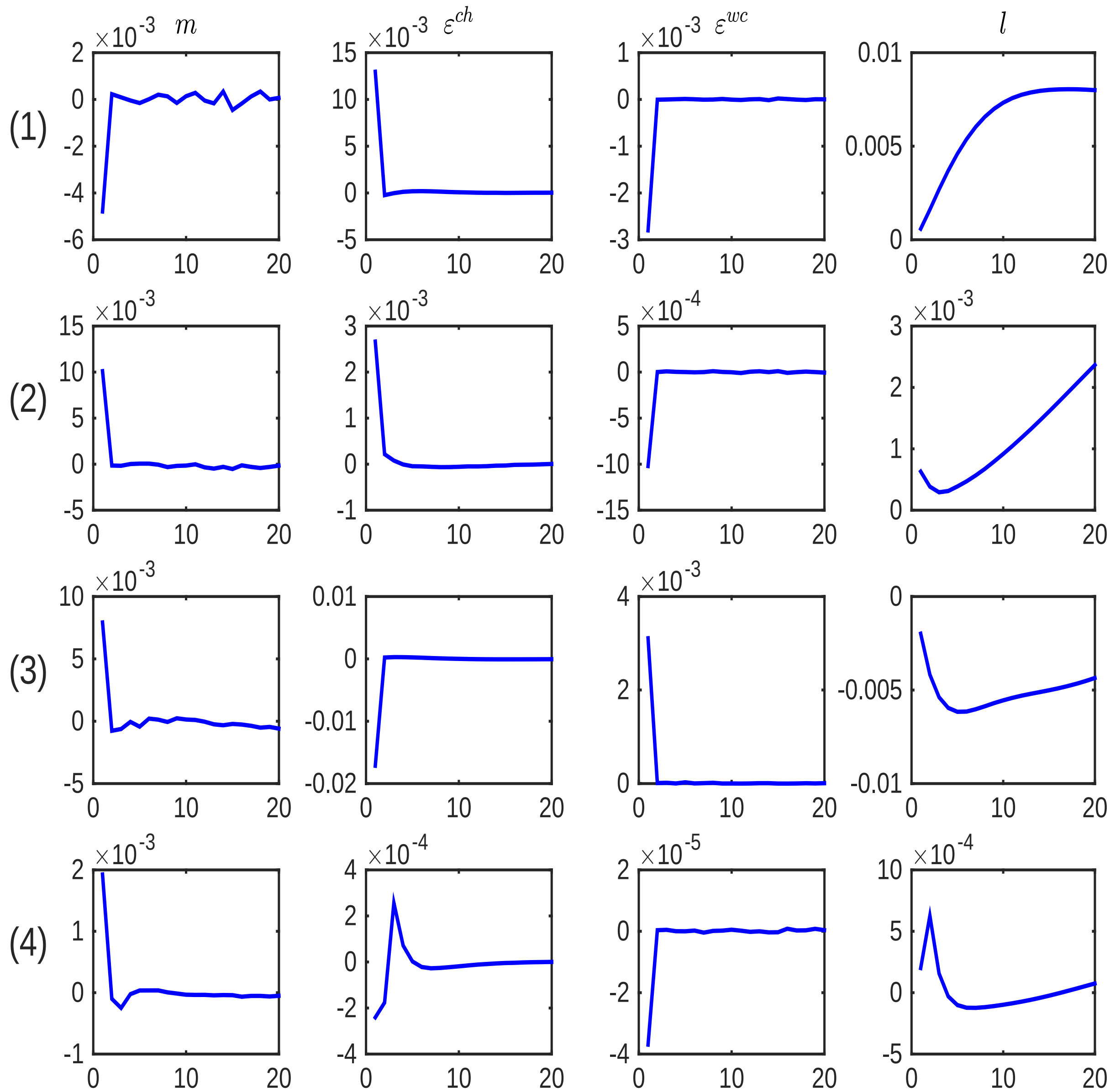

Table 1: **Calibrated Parameters**

The table reports the calibrated parameter values.

Parameter	Description	Value
δ	Depreciation rate	0.025
g	Government consumption to GDP ratio	0.20
β	Discount factor	0.994
ϕ	Curvation on disutility of labor	1
λ_w	Markup in the labor market	1.05
λ_p	Markup in the intermediate good market	1.20
μ_z	Steady state growth rate of neutral technology	0.41
μ_ψ	Steady state growth rate of investment specific technology	0.42
$1-\gamma_e$	Fraction of entrepreneurial net worth transferred to households	1-0.985
μ_b	Bankruptcy cost parameter	0.30
$F(\bar{\omega})$	Steady state probability of default	0.008

Table 2: **Parameters**

This table reports the prior means and standard deviations, bounds, and the posterior means and standard deviations of the parameter values estimated using the Bayesian Markov Chain Monte Carlo method based on 50,000 Monte Carlo iterations. The prior distribution for all the parameters is normal. Panel A includes economic parameters and Panel B includes parameters describing the property of the shocks. The sample period is 1957Q2 - 2015Q4.

		Prior			Posterior		
Parameters	Description	Mean	Std. Dev.	Bounds	Mode	Std. Dev.	[5%, 95%]
Panal A: Economic Parameters							
ψ	Inverse of EIS	0.50	0.20	[0.00, 100.00]	0.82	0.0007	[0.8168, 0.8190]
γ	Risk aversion	10.00	5.00	[1.00, 300.00]	5.23	0.1308	[5.0793, 5.4527]
b	Habit parameter	0.50	0.10	[0.00, 1.00]	0.65	0.0037	[0.6459, 0.6573]
α	Power on capital in production function	0.50	0.25	[0.00, 1.00]	0.17	0.0004	[0.1735, 0.1751]
ξ_p	Price stickiness	0.50	0.10	[0.00, 1.00]	0.78	0.0035	[0.7753, 0.7863]
ξ_w	Wage stickiness	0.75	0.10	[0.00, 1.00]	0.93	0.0004	[0.9271, 0.9284]
σ_a	Curvature of utilization cost	1.00	1.00	[0.00, 10.00]	4.21	0.7303	[3.0371, 5.4590]
σ_s	Curvature of investment adjustment cost	5.00	3.00	[0.00, 30.00]	1.48	0.0572	[1.3774, 1.5741]
ϕ_r	Policy smoothing parameter	0.75	0.10	[0.00, 1.00]	0.78	0.0011	[0.7758, 0.7791]
ϕ_y	Policy weight on output growth	0.25	0.10	[0.00, 2.00]	0.63	0.0248	[0.5957, 0.6699]
ϕ_π	Policy weight on inflation	1.50	0.25	[1.01, 5.00]	1.55	0.0026	[1.5411, 1.5502]
ℓ	Price indexing weight on inflation target	0.50	0.15	[0.00, 1.00]	0.08	0.0193	[0.0562, 0.1230]
ℓ_w	Wage indexing weight on inflation target	0.50	0.15	[0.00, 1.00]	0.33	0.0011	[0.3334, 0.3370]
ℓ_μ	Price indexing weight on technology growth	0.50	0.15	[0.00, 1.00]	0.50	0.1523	[0.2529, 0.7527]
Panal B: Shock Parameters							
$\bar{\sigma}$	Steady state value of Risk shock	0.02	0.02	[0.00, 2.00]	0.13	0.0032	[0.1250, 0.1352]
ρ_z	Autocorrelation, NT shock	0.50	0.10	[0.00, 1.00]	0.23	0.0059	[0.2193, 0.2385]
ρ_ψ	Autocorrelation, IST shock	0.50	0.10	[0.00, 1.00]	0.55	0.0025	[0.5479, 0.5559]
ρ_r	Autocorrelation, MP shock	0.50	0.10	[0.00, 1.00]	0.58	0.0028	[0.5781, 0.5870]
ρ_o	Autocorrelation, Risk shock	0.50	0.10	[0.00, 1.00]	0.57	0.0488	[0.4866, 0.6527]
σ_z (%)	Std. Dev., NT shock	0.50	0.10	[0.00, 100.00]	0.46	0.0017	[0.4522, 0.4580]
σ_ψ (%)	Std. Dev., IST shock	0.50	0.10	[0.00, 100.00]	0.35	0.0011	[0.3502, 0.3533]
σ_r (%)	Std. Dev., MP shock	0.50	0.10	[0.00, 100.00]	0.14	0.0022	[0.1366, 0.1428]
σ_o (%)	Std. Dev., Risk shock	2.00	0.50	[0.00, 100.00]	4.22	0.3344	[3.7205, 4.7922]

Table 3: **Goodness of Model Fit**

This table presents the summary statistics of the model-implied variables and their counterparts in the data. Panel A includes the nine macroeconomic variables used in the estimation: output growth (dy), consumption growth (dc), investment growth (di), hours per capita scaled by sample mean (h), growth of relative price of consumption to investment (μ_ψ), inflation ($\tilde{\pi}$), 3-month T-bill (r), growth of credit (db), and credit spread (cs). Panel B presents the summary statistics of model return on capital and its empirical counterpart, the return on market portfolio. The last row presents the mean and standard deviation of the investment adjustment cost to output ratio (IAC/Y) in the model and the range of its value reported in the empirical literature. The reported values of Inflation, 3-month T-bill, credit spread, return on capital and return on market portfolio are annualized based on values in quarterly frequency. Data are quarterly from 1957Q2 to 2015Q4.

	Data		Model			
	Mean (%)	Std. Dev. (%)	Mean (%)	Std. Dev. (%)	*Corr*	p-value
Panel A: Macroeconomic variables used in the estimation						
dy	0.40	0.88	0.34	0.77	0.83	0.00
dc	0.48	0.54	0.35	0.57	0.61	0.00
di	0.38	3.21	0.25	2.90	0.77	0.00
h	0.00	4.90	0.00	4.89	1.00	0.00
μ_ψ	0.42	1.20	0.40	0.56	0.18	0.01
π	3.26	2.34	3.89	2.02	0.93	0.00
r	5.13	3.59	7.79	1.52	0.72	0.00
db	0.73	0.99	0.35	0.61	0.57	0.00
cs	1.95	0.82	0.41	0.61	0.80	0.00
Panel B: Model-implied Financial variables						
R_k	6.63	33.77	5.86	7.36	0.23	0.00
IAC/Y	0-4.6		0.24	0.48		

Table 4: **Correlation matrix of model-implied shocks**

This table reports the correlation matrix of four model-implied shocks (Panel A), and their correlations with six return factors and three empirical measures of IST shocks (Panel B). The four model-implied shocks are NT, IST, MP, and Risk shocks. Six return factors are the Fama and French five factors, including market access return (MKT), small minus big (SMB), high minus low (HML), robust minus weak (RMW), conservative minus aggressive (CMA) and momentum (MOM) factors. P-values of the correlation coefficients are reported in parenthesis.

Panel A.

	NT	IST	MP	Risk
NT	1.000	-0.353	0.098	0.036
	(0.000)	(0.000)	(0.135)	(0.583)
IST	-0.353	1.000	-0.259	-0.147
	(0.000)	(0.000)	(0.000)	(0.024)
MP	0.098	-0.259	1.000	-0.071
	(0.135)	(0.000)	(0.000)	(0.276)
Risk	0.036	-0.147	-0.071	1.000
	(0.583)	(0.024)	(0.276)	(0.000)

Panel B.

	Return Factors						IST Measures		
	MKT	SMB	HML	RMW	CMA	MOM	Ishock	IMC	gIMC
NT	0.200	0.050	-0.107	0.052	-0.146	-0.186	-0.122	0.114	-0.064
	(0.004)	(0.467)	(0.124)	(0.451)	(0.035)	(0.004)	(0.069)	(0.090)	(0.339)
IST	-0.116	0.010	0.023	-0.027	0.051	0.013	0.203	0.029	0.026
	(0.094)	(0.887)	(0.740)	(0.693)	(0.458)	(0.846)	(0.002)	(0.667)	(0.699)
MP	-0.070	-0.158	0.034	0.056	0.065	0.058	-0.165	-0.247	-0.241
	(0.315)	(0.022)	(0.621)	(0.421)	(0.348)	(0.373)	(0.014)	(0.000)	(0.000)
Risk	-0.078	-0.099	0.013	-0.011	0.072	-0.022	-0.032	0.001	0.025
	(0.258)	(0.153)	(0.849)	(0.871)	(0.298)	(0.738)	(0.636)	(0.990)	(0.715)

Table 5: **Risk premium of model-implied shocks**

This table reports the estimated risk premia (in percentage) of four model-implied shocks via the two-step Fama-Macbeth cross-sectional regressions. In Panel A, the test assets are the value-weighted ten size, ten book-to-market, ten momentum, and ten industry portfolios. In Panel B, the test assets are the value-weighted ten size, ten book-to-market, ten momentum, ten investment, ten operating profitability, and ten industry portfolios. We consider both univariate model for each shock and multivariate model with all four shocks included. The t-statistics adjusted for autocorrelation and heteroscedasticity following Newey and West (1987) are reported in parenthesis.

Panel A.

	NT	IST	MP	Risk	AvgR2
1	1.69				0.55
	(6.53)				
2		-3.95			0.53
		(-6.73)			
3			-2.20		0.51
			(-6.59)		
4				-3.88	0.53
				(-6.78)	
5	0.25	-2.64	0.15	-1.10	0.65
	(1.03)	(-6.18)	(0.63)	(-3.61)	

Panel B.

	NT	IST	MP	Risk	AvgR2
1	1.76				0.58
	(6.46)				
2		-3.89			0.56
		(-6.64)			
3			-2.37		0.53
			(-6.49)		
4				-3.69	0.56
				(-6.66)	
5	0.32	-2.47	-0.09	-0.58	0.66
	(1.39)	(-5.85)	(-0.34)	(-2.73)	

Table 6: **Portfolio returns and factor loadings on model-implied shocks**

This table reports the quarterly average portfolio returns (in percentage) and their factor loadings on the four model-implied shocks. Panel A and B present results for decile portfolios sorted on size and book-to-market, respectively. Betas are estimated using the full-sample from 1957q2 to 2015q4. The t-statistics adjusted for autocorrelation and heteroscedasticity following Newey and West (1987) are reported in parenthesis.

Panel A. Size portfolios	R	$Beta_{NT}$	$Beta_{IST}$	$Beta_{MP}$	$Beta_{Risk}$
Small	3.70	2.02	-0.88	-3.03	-1.86
	(5.00)	(2.29)	(-0.96)	(-3.53)	(-2.22)
2	3.52	1.78	-1.08	-2.41	-1.63
	(5.41)	(2.12)	(-1.23)	(-2.95)	(-2.04)
3	3.70	1.71	-0.97	-2.24	-1.36
	(6.59)	(2.15)	(-1.16)	(-2.89)	(-1.80)
4	3.49	1.50	-1.03	-2.18	-1.40
	(6.19)	(1.95)	(-1.29)	(-2.92)	(-1.91)
5	3.52	1.73	-0.81	-2.02	-1.27
	(6.58)	(2.34)	(-1.04)	(-2.81)	(-1.81)
6	3.37	1.54	-0.63	-1.59	-1.04
	(6.72)	(2.23)	(-0.88)	(-2.35)	(-1.58)
7	3.38	1.57	-0.76	-1.63	-1.20
	(6.73)	(2.27)	(-1.05)	(-2.42)	(-1.83)
8	3.25	1.49	-0.63	-1.26	-0.89
	(7.16)	(2.25)	(-0.92)	(-1.96)	(-1.42)
9	3.05	1.41	-0.48	-1.27	-1.04
	(6.79)	(2.36)	(-0.77)	(-2.17)	(-1.83)
Big	2.62	1.34	-0.68	-1.05	-0.56
	(5.13)	(2.49)	(-1.22)	(-1.99)	(-1.08)
Small-Big	1.09	0.68	-0.20	-1.99	-1.31
	(1.76)	(1.06)	(-0.30)	(-3.19)	(-2.15)
Panel B. Book-to-Market portfolios					
Low	2.63	2.13	-0.59	-1.26	-0.75
	(4.67)	(3.20)	(-0.85)	(-1.94)	(-1.19)
2	2.87	1.41	-0.65	-1.13	-0.67
	(5.85)	(2.30)	(-1.01)	(-1.89)	(-1.15)
3	2.92	1.18	-0.84	-1.09	-0.56
	(6.61)	(1.99)	(-1.35)	(-1.90)	(-0.99)
4	2.89	0.96	-0.61	-1.32	-0.45
	(6.19)	(1.61)	(-0.97)	(-2.28)	(-0.80)
5	2.94	0.96	-0.72	-1.22	-0.85
	(6.46)	(1.74)	(-1.25)	(-2.27)	(-1.61)
6	3.22	1.04	-0.53	-1.15	-0.70
	(7.52)	(1.91)	(-0.93)	(-2.16)	(-1.35)
7	3.03	0.91	-0.42	-1.55	-0.84
	(5.77)	(1.52)	(-0.66)	(-2.64)	(-1.47)
8	3.39	1.02	-0.71	-1.31	-1.10
	(7.25)	(1.63)	(-1.09)	(-2.14)	(-1.84)
9	3.84	1.29	-0.71	-1.54	-0.53
	(7.94)	(1.99)	(-1.04)	(-2.45)	(-0.86)
High	3.99	1.68	-0.97	-2.85	-1.27
	(6.88)	(2.11)	(-1.16)	(-3.67)	(-1.68)
High-Low	1.36	-0.44	-0.38	-1.59	-0.52
	(2.21)	(-0.69)	(-0.56)	(-2.55)	(-0.86)

Table 7: **Expected cross-sectional return spreads predicted by model-implied shocks**

This table reports the expected cross-sectional return spreads (in percentage) for six cross sections, including value-weighted size, book-to-market, investment, earnings, momentum, and long-term reversal decile portfolios. Panel A presents the average quarterly cross-sectional return spreads (R), t-statistics of R (t(R)), expected cross-sectional return spreads (ER), the ratio of ER/R, the difference between R and ER (effectively the alpha of the model), and t-statistics of the difference (t(diff)). The expected risk premium due to the exposure to a risk factor is calculated as the risk exposure times the risk premium of the corresponding risk factor ($\beta_i\lambda_i$). The risk exposures are estimated from the full sample from 1957q2 and 2015q4. The risk premia of risk factors are estimated using the multivariate model as Panel A in Table 5. ER is calculated as the summation of the expected risk premia from all four model-implied shocks, $ER = \sum_i \beta_i\lambda_i,\ i = NT,\ IST,\ MP,\ and\ Risk$. Panel B presents the expected risk premium due to the exposure to each shock, respectively. The t-statistics adjusted for autocorrelation and heteroscedasticity following Newey and West (1987) are reported in parenthesis.

Panel A.

	R	t(R)	ER	ER/R	ER-R	t(diff)	α_{mkt}	$t(\alpha_{mkt})$	α_{ff3}	$t(\alpha_{ff3})$	α_{ff5}	$t(\alpha_{ff5})$	α_q	$t(\alpha_q)$
SIZE(s-b)	1.09	1.76	1.82	167.6%	-0.73	1.19	0.50	0.85	-0.20	-0.90	0.00	0.00	0.21	0.61
BM(h-l)	1.36	2.21	1.22	89.5%	0.14	0.23	1.28	1.91	-0.76	-2.84	-0.30	-1.06	0.22	0.34
INV(l-h)	1.35	3.05	0.71	52.6%	0.64	1.45	1.61	3.43	0.66	1.75	0.08	0.24	-0.15	-0.46
EP(h-l)	1.28	2.40	0.88	68.8%	0.40	0.75	1.50	2.73	0.01	0.02	-0.14	-0.37	0.15	0.22
MOM(h-l)	3.94	4.97	0.54	13.8%	3.39	4.29	4.51	6.54	5.32	7.24	4.83	4.86	2.03	1.54
LT(l-h)	1.13	1.75	1.00	88.5%	0.13	0.20	1.09	1.72	-0.45	-0.86	-0.23	-0.44	0.52	0.80

Panel B.

	$\beta_{NT}\lambda_{NT}$	$\beta_{IST}\lambda_{IST}$	$\beta_{MP}\lambda_{MP}$	$\beta_{Risk}\lambda_{Risk}$	$\beta_{NT}\lambda_{NT}/R$	$\beta_{IST}\lambda_{IST}/R$	$\beta_{MP}\lambda_{MP}/R$	$\beta_{Risk}\lambda_{Risk}/R$
SIZE(s-b)	0.17	0.52	-0.30	1.44	15.3%	47.8%	-27.9%	132.4%
BM(h-l)	-0.11	0.99	-0.24	0.58	-8.0%	73.0%	-17.9%	42.3%
INV(l-h)	-0.18	0.77	0.04	0.08	-13.3%	57.1%	2.8%	6.0%
EP(h-l)	-0.20	0.53	-0.03	0.59	-16.0%	41.4%	-2.4%	45.8%
MOM(h-l)	-0.53	1.17	0.14	-0.23	-13.5%	29.7%	3.5%	-5.9%
LT(l-h)	0.02	0.32	-0.06	0.71	1.8%	28.7%	-5.5%	63.5%