News Shock, Long-Run Risk, and Asset Returns*

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December, 2016

Abstract

This paper studies the long-run risk embedded in the news about future investment-specific technology (IST). The IST news shock, which reflects future technological improvements in the production of investment goods such as computers, machines, and equipment, causes persistent future consumption growth, explains a large share of business cycle fluctuations in macro aggregates, and affects stock returns through the channel of expected cash flow growth. Consistent with the long-run consumption risk hypothesis, we find that the IST news shock carries a significantly positive risk premium in the cross section of asset returns and drives firm cash flows over long horizons.

JEL classification codes: G10, G12
Keywords: news shock, long-run risk, stock returns, technology shock, consumption based asset pricing model

*The paper builds on and extends a preliminary draft titled "News Shock and Long-Run Consumption Risk" by Chang Joo Lee. We thank Robert Chirinko, Lawrence Christiano, Anna Cieslak, Dimitris Papanikolaou, Jonathan Parker, Giorgio Primiceri, Annette Vissing-Jorgensen, and seminar participants at Kellogg School of Management and UIC for advice and helpful comments. We thank John Fernald, Hashmat Khan, and Eric Sims for providing us with their data files.

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1 Introduction

One of the fundamental goals in finance literature is to relate the behavior of expected returns to the real economy (Fama (1991)). To this end, many existing studies focus on asset pricing models expressed in terms of innovations to endogenous macro variables, such as consumption and dividend. While these reduced-form approaches can succinctly describe the risk-return trade-off investors face, they provide limited explanation on why returns are tied to macro variables in equilibrium. To understand the relation between returns and macro variables, we should redirect our attention to exogenous fundamental shocks driving the macroeconomy and the financial market. In this paper, we assess the asset pricing implications of shocks to expected future productivity, which have been shown to be an important source of macroeconomic fluctuations, in the context of long-run consumption risk.

Since Bansal and Yaron (2004) proposed an economy where agents care about future consumption prospects, many studies have found empirical success in explaining cross-sectional and aggregate stock returns using long-run consumption risk (Parker and Julliard (2005); Hansen, Heaton and Li (2008); Malloy, Moskowitz and Vissing-Jorgensen (2009); Xiao, Faff, Gharghori and Min (2013); Jagannathan and Marakani (2015) and others). Further analysis shows that long-run consumption risk is embedded not only in stock returns but also in firm cash flows (Bansal, Dittmar and Lundblad (2005);Bansal, Dittmar and Kiku (2007)) and that the compensation for long-run risk is concentrated in its business cycle component (Boons and Tamoni (2016)). The lesson from these studies is that there are fundamental causes which generate long-run consumption growth, drive business cycles, affect firm cash flows, and also contribute to equity risk premia.

This paper proposes that news about future investment-specific technology (IST) is one important fundamental cause of these related results. We document that IST news shocks are a prominent source of long-run consumption risk and business cycle fluctuations, and affect stock returns through the channel of expected cash flow growth. As a result, investors require a risk premium for holding assets with cash flows more exposed to IST news shocks in the cross section of stock returns.

An investment-specific technology shock refers to technological improvements in the production of investment goods such as computers, machines, and heavy equipment. Empirical evidence suggests that IST shocks are an important source of aggregate fluctuations (Greenwood, Hercowitz and Krusell (1997); Fisher (2006)). In particular, recent studies find that IST news shocks, which reflect anticipated changes in future IST, explain the majority of economic fluctuations at business cycle frequencies (Ben Zeev and Khan (2015); Ramey (2016)). Traditional IST shocks (IST current shocks) affect the technology in investment good production in the same period during which the shock occurs. In contrast, IST news shocks have no contemporaneous effect on IST. Instead, they reflect IST changes in the future. For example, suppose a firm invents a new method to produce computer chips at a lower cost. Since the firm needs to upgrade its machines and educate its employees to implement the new method, the invention will not affect computer chip production in the current period. However, people will expect computer chips to be cheaper in the near future and will increase their consumption and investment accordingly in the current period. As the new technology becomes implemented in the production process, it increases consumption, investment, and output further, generating aggregate fluctuations, inducing long-run consumption growth, and affecting the cash flows of firms that benefit from cheaper computer chips.

The importance of IST news shocks in business cycle fluctuations and long-run consumption risk is displayed in Figure 1, which plots the four-quarter moving average of the identified IST news shock (left axis) – to be explained later – and realized future long-run consumption growth (right axis) over the period from 1961Q4 to 2011Q4. The realized long-run consumption growth is calculated as the discounted sum of actual consumption growth over the next 16 quarters. The vertical lines represent the starting and ending points of NBER recessions. The figure shows that the IST news shock and realized long-run consumption growth tend to comove over business cycles. They are both high in the beginning of expansions and low in the beginning of recessions. This suggests that IST news shocks are an important driving force of both business cycles and long-run consumption growth.

We use the framework of Hansen, Heaton and Li (2008) in which the state of the economy evolves according to a vector autoregression (VAR) perturbed by fundamental shocks and the representative agent has the recursive preferences of Epstein and Zin (1989). Following Malloy et al. (2009), we focus on the special case with EIS equal to one. Under this condition, the stochastic discount factor (SDF) is a function of fundamental shocks and the effect of a fundamental shock on the SDF can be expressed in terms of the changes in long-run consumption growth due to the shock. Therefore, the asset pricing implications of the IST news shock can be inferred from the impulse response of consumption to the IST news shock.

We identify the IST news shock from VAR residuals using the maximum forecast error variance (MFEV) method developed by Uhlig (2004) and applied to news shock identification by Barsky and Sims (2011) and Ben Zeev and Khan (2015). This identification strategy does not require a strong stand about the underlying general equilibrium model and has been used by Barsky and Sims (2012) and Kurmann and Otrok (2013). Utilizing the assumption that the investment-specific technology process is driven only by IST current shocks and IST news shocks, the identification method recovers the IST news shock as the shock that has no impact on IST in the current period but best explains the future movements of IST.

The identification result shows that the IST news shock is an important source of business cycle fluctuations and long-run consumption growth. For example, a positive IST news shock raises consumption, investment, output, and hours over long horizons. Specifically, a positive one-standard-deviation IST news shock increases consumption by 0.56% over a 10 year horizon. Also, the IST news shock accounts for the majority of forecast error variance of macro aggregates at business cycle frequencies. In particular, between 50% and 60% of consumption forecast error variance is attributable to the IST news shock at 2 to 10 year horizons. The impulse response of consumption implies that the SDF of our economy decreases significantly upon a positive IST news shock. This result indicates that IST news shocks are an important contributor to the risk premium of long-run consumption risk documented in the literature.

Consistent with this implication, the asset pricing test shows that the IST news shock carries a significant risk premium in the cross section of stock returns. We find that firms with high IST news shock betas tend to have higher returns on average than firms with low betas. Furthermore, the cash flows of firms with high IST news shock betas are more sensitive to IST news shock than those with low betas. This evidence is consistent with the findings of Bansal et al. (2005) who show that firms' cash flow betas with innovations in persistent consumption growth determine cross-sectional risk premia. We also show that the risk premium on the IST news shock is positive and statistically significant in the cross section of 30 portfolios sorted on IST news shock beta, book-to-market, and size. This finding is in agreement with Parker and Julliard (2005) and Malloy et al. (2009), who document that long-run consumption risk is priced in the portfolios sorted on size and book-to-market.

In summary, our paper provides evidence that the IST news shock is one common thread across business cycles, long-run consumption risk, and firms' cash flow growth and, as a result, is significantly priced in the financial market.

Our paper is related to long-run risk literature pioneered by Bansal and Yaron (2004), who show that shocks to long-run consumption growth can explain the equity risk premium. Parker and Julliard (2005) show that the exposure of an asset's return to consumption growth over the three years following the return accounts for the cross section of Fama French 25 portfolio average returns. Malloy et al. (2009) find that long-run stockholder consumption risk can explain the cross-sectional differences in asset returns with more plausible risk aversion estimates than long-run aggregate consumption risk. Xiao et al. (2013) investigate a two-factor asset pricing model with current consumption growth and market returns, where the market returns are a proxy for news about future consumption growth, and Jagannathan and Marakani (2015) suggest a novel method to identify long run consumption growth from the cross section of dividend price ratios.

Recent literature emphasizes the business cycle component of long-run risk. Boons and Tamoni (2016) argue that the exposure in long-term returns to business cycle growth is important in the cross section of asset returns. Also, Boons (2016) finds that financial state variables which predict economic fluctuations over the next five years are priced in the cross section of asset returns. The results of our paper suggest that we can connect these findings through the IST news shock, a common exogenous cause that is economically meaningful for business cycle fluctuations in consumption and other macro aggregates.

We also contribute to the literature relating asset returns to technology shocks. Kaltenbrunner and Lochstoer (2010) show that in an economy with capital adjustment costs, agents slowly adjust their consumption after a technology shock, and therefore technology shocks can raise long-run consumption risk. Croce (2014) shows that shocks to long-run productivity growth combined with recursive preferences and investment frictions can generate key features of asset prices and macroeconomic quantities observed in the data. Our paper reinforces their arguments, as we empirically show that the IST news shock affects productivity as well as consumption over long horizons. Furthermore, technology shocks have been shown to explain other stylized patterns of the financial market. Papanikolaou (2010) examines the asset pricing implications of a general equilibrium model with investment sector technology shocks, and shows that the covariance of asset returns with investment shocks can explain the average returns of high book-to-market stocks and low book-to-market stocks. Kurmann and Otrok (2013) suggest that the endogenous response of monetary policy to total factor productivity (TFP) news shocks is the main driver of the slope of term structure. Malkhozov and Tamoni (2015) explore a dynamic stochastic general equilibrium (DSGE) model with TFP and IST technology shocks and propose that news shocks are important in explaining why stock-market valuations and excess returns lead the business cycle. Our results suggest that IST news shocks are another important technology shocks in the cross section of asset returns as a salient source of long-run consumption risk and cash flow risk.

Lastly, our paper contributes to the literature investigating firms' cash flow risk. Hansen et al. (2008) provide a formal framework with which to measure the exposure of long-term cash flow growth to macroeconomic fluctuations and show that this long-run cash flow risk explains the value premium. Bansal et al. (2005) show that cash flow consumption beta, the projection coefficient of cash flow news onto innovations in long-run consumption growth, determines the cross-sectional risk premia of book-to-market, momentum, and size sorted portfolios. Bansal, Dittmar and Kiku (2007) find that the risk premia of book-to-market and size sorted portfolios can be explained by the difference in the cointegrating relation between portfolio dividends and consumption. These findings suggest that there exist common stochastic trends between firm cash flows and consumption and that innovations in these common trends are priced in the financial market. We contribute to this literature by proposing that the IST news shock is an exogenous cause for the common stochastic trends.

The remainder of this paper is organized as follows. In Section 2, we derive the Euler equation in terms of the underlying fundamental shocks. In Section 3, we explain the methodology to identify the IST news shock. Section 4 describes the data. In Section 5, we report the identification results and show that the IST news shock is an important source of long-run consumption risk. In Section 6, we explore the implications of the IST news shock for asset prices. Section 7 concludes the paper.

2 Structural Asset Pricing Model

In this section, we derive the stochastic discount factor in terms of the underlying fundamental shocks. The theoretical setup closely follows that of Hansen, Heaton and Li (2008). When agents have recursive preferences with EIS = 1 and fundamental shocks are conditionally normal and homoskedastic, the log stochastic discount factor is a linear function of fundamental shocks.

2.1 State of the Economy

The log-linearized equilibrium of the economy can be expressed in a state space form as follows:

$$x_t = Gx_{t-1} + H\varepsilon_t \tag{1}$$

$$z_t = Ux_{t-1} + V\varepsilon_t. \tag{2}$$

Here, x_t is an $n \times 1$ vector of a constant and $n-1$ time varying state variables, and ε_t is a $k \times 1$ vector of fundamental shocks, such as shocks to technologies, and potential measurement errors. z_t is a $k \times 1$ vector of observable variables.[1] The vector z_t typically includes growth rates of non-cointegrated I(1) observable variables, error correction variables from cointegrating relationships, and I(0) observable variables. The matrix G has eigenvalues less than 1 in absolute values except for a single unit eigenvalue associated with a constant state variable. Let $E_t[\cdot] = E[\cdot|\{x_{t-s}, z_{t-s}\}_{s=0}^{\infty}]$ be the conditional expectation operator for the agents in the economy, and $E_{z,t}[\cdot] = E[\cdot|\{z_{t-s}\}_{s=0}^{\infty}]$ be the conditional expectation operator for the econometrician who observes only present and past realizations of the observables. We assume that ε_t is conditionally normal and homoskedastic, and that it satisfies $E_{t-1}[\varepsilon_t] = \mathbf{0}_k$, $E_{t-1}[\varepsilon_t \varepsilon_t'] = I_k$, $E_{t-1}\left[\varepsilon_{t+s}\varepsilon_{t+h}'\right] = \mathbf{0}_{k\times k}$ for $s \neq h$, where $\mathbf{0}_k$ is a $k \times 1$ vector of zeros, I_k is a k-dimensional identity matrix, and $\mathbf{0}_{k\times k}$ is a $k \times k$ matrix of zeros.

We can calculate the impulse response functions of observables at time $t+h$ to the shocks at time t by substituting (1) into (2) repeatedly:

$$E_t[z_{t+h}] - E_{t-1}[z_{t+h}] = \begin{cases} V\varepsilon_t & \text{for } h = 0 \\ UG^{h-1}H\varepsilon_t & \text{for } h \geq 1. \end{cases} \tag{3}$$

Note that (3) is what agents believe will happen to z in the future if ε occurs at time t. Since asset prices reflect agents' beliefs about future consumption and payoffs, we use the expectation operator for agents in solving for the stochastic discount factor.

Suppose that log consumption growth, $\Delta c_t = \log(C_t) - \log(C_{t-1})$, is the j-th variable in z_t. Then the impulse response function of log consumption growth is

$$E_t[\Delta c_{t+h}] - E_{t-1}[\Delta c_{t+h}] = \begin{cases} \mathbf{e}_j' V\varepsilon_t & \text{for } h = 0 \\ \mathbf{e}_j' UG^{h-1}H\varepsilon_t & \text{for } h \geq 1, \end{cases} \tag{4}$$

where $\mathbf{e}_j$ is the $k \times 1$ selection vector with one in the j-th place and zeros elsewhere.

[1] For convenience, we assume that ε_t and z_t are both $k \times 1$ vectors. In general, they do not need to be have the same size. See Fernández-Villaverde, Rubio-Ramírez, Sargent and Watson (2007).

2.2 Euler Equations

Our asset pricing model is based on Epstein and Zin (1989) recursive preferences. A representative agent in the economy has the time t utility of the form

$$V_t = \left\{ (1-\beta) C_t^{1-\frac{1}{\sigma}} + \beta \left(E_t \left[V_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\sigma}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\sigma}}}, \quad (5)$$

where the variable V_{t+1} is the continuation value of a consumption stream from time $t+1$ and on, $\gamma\,(>0)$ is the coefficient of relative risk aversion, $\beta\,(\in(0,1))$ is the time-preference parameter, and $\sigma\,(>0)$ is the elasticity of intertemporal substitution (EIS).

Following Malloy, Moskowitz and Vissing-Jorgensen (2009), we assume that the elasticity of intertemporal substitution is equal to unity. The asset pricing test in Parker and Julliard (2005) also implicitly assumes EIS $=1$. Hansen et al. (2008) show that when the recursive preferences have EIS $=1$, the stochastic discount factor (SDF) depends only on the discounted impulse responses of consumption growth. Specifically, the logarithm of one period ahead SDF, $s_{t|t-1} = \log\left(S_{t|t-1}\right)$, with EIS $=1$ is given by

$$\begin{aligned} s_{t|t-1} &= \log\beta - (c_t - c_{t-1}) + (1-\gamma)\left[[E_t - E_{t-1}] \left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h} \right) \right] \\ &\quad - \frac{(1-\gamma)^2}{2} Var_{t-1}\left([E_t - E_{t-1}] \left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h} \right) \right), \end{aligned} \quad (6)$$

where $c_t = \log(C_t)$.

The assumption EIS $=1$ implies that if γ is bigger than 1, an increase in expected long-run consumption growth $\left([E_t - E_{t-1}]\left(\sum_{h=0}^{\infty}\beta^h \Delta c_{t+h}\right) > 0\right)$ lowers the SDF. In other words, EIS $=1$ automatically assumes that fundamental shocks incurring positive long-run consumption growth earn positive risk premia with a reasonable range of γ. This implication is consistent with existing empirical findings that assets that covary more with long-run consumption growth earn higher average returns.

Using the consumption impulse response function (4) from the previous section, we rewrite the SDF (6) in terms of the underlying fundamental shocks:

$$\begin{aligned} [E_t - E_{t-1}] \left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h} \right) &= \mathbf{e}_j' \left\{ V + \sum_{h=1}^{\infty} \left(\beta^h U G^{h-1} H \right) \right\} \varepsilon_t \\ &= \lambda(\beta)' \varepsilon_t, \end{aligned} \quad (7)$$

where $\lambda(\beta)' = \mathbf{e}_j' \left\{ V + \sum_{h=1}^{\infty} \left(\beta^h U G^{h-1} H \right) \right\}$. Note that $\lambda(\beta)$ is well defined given the restrictions on G and β. From the properties of ε_t, we have

$$Var_{t-1}\left([E_t - E_{t-1}]\left(\sum_{h=0}^{\infty}\beta^h \Delta c_{t+h}\right)\right) = \lambda(\beta)' E_{t-1}\left[\varepsilon_t \varepsilon_t'\right]\lambda(\beta) = |\lambda(\beta)|^2 . \tag{8}$$

Substituting (7), (8), and (4) for $h = 0$ into (6), we get

$$\begin{aligned} s_{t|t-1} &= \bar{b} - \left\{\mathbf{e}_j'\left(Ux_{t-1} + V\varepsilon_t\right)\right\} + (1-\gamma)\,\lambda(\beta)'\,\varepsilon_t \\ &= \bar{b} - \mathbf{e}_j' U x_{t-1} + \left\{-\lambda_0' + (1-\gamma)\,\lambda(\beta)'\right\}\varepsilon_t, \end{aligned} \tag{9}$$

where $\lambda_0' = \mathbf{e}_j' V$ and $\bar{b} = log\beta - \frac{(1-\gamma)^2}{2}|\lambda(\beta)|^2$. Note that the logarithm of one period ahead SDF is conditionally normal:

$$\begin{aligned} E_{t-1}\left[s_{t|t-1}\right] &= \bar{b} - \mathbf{e}_j' U x_{t-1} \\ Var_{t-1}\left[s_{t|t-1}\right] &= \left|-\lambda_0 + (1-\gamma)\,\lambda(\beta)\right|^2 . \end{aligned}$$

Using the SDF (9), we can express the asset pricing model in terms of the fundamental shocks. The time $t-1$ conditional Euler equation for asset i states that

$$E_{t-1}\left[S_{t|t-1} R_{i,t}\right] = 1. \tag{10}$$

Equation (10) implies that the excess return on asset i satisfies

$$E_{t-1}\left[R_{i,t} - R_{f,t}\right] = -Cov_{t-1}\left(\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]}, R_{i,t} - R_{f,t}\right), \tag{11}$$

where

$$\begin{aligned} \frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]} &= \frac{\exp\left(s_{t|t-1}\right)}{E_{t-1}\left[\exp\left(s_{t|t-1}\right)\right]} \\ &= \exp\left(\left\{-\lambda_0' + (1-\gamma)\,\lambda(\beta)'\right\}\varepsilon_t - \frac{1}{2}\left|-\lambda_0 + (1-\gamma)\,\lambda(\beta)\right|^2\right) \end{aligned} \tag{12}$$

Note that time $t-1$ state variables do not appear in Equation (11). Taking unconditional expectations on both sides of (11) and using the property

$$Cov\left(A_t, B_t\right) = E\left[Cov_{t-1}\left(A_t, B_t\right)\right] + Cov\left(E_{t-1}\left[A_t\right], E_{t-1}\left[B_t\right]\right),$$

we get the unconditional asset pricing equation for the excess return on asset i:

$$E\left[R_{i,t} - R_{f,t}\right] = -Cov\left(\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]}, R_{i,t} - R_{f,t}\right). \tag{13}$$

Equation (13) in conjunction with (12) provides an asset pricing model of the long-run consumption hypothesis, expressed in terms of fundamental shocks. It states that when agents have recursive preferences with EIS = 1 and fundamental shocks are conditionally normal and homoskedastic, the unconditional Euler equation simplifies to an asset pricing model where the SDF depends only on the fundamental shocks. Moreover, the risk-return trade off of a fundamental shock depends on its impact on future consumption growth and the preference parameters β and γ. For example, suppose that consumption grows gradually in response to a fundamental shock until it reaches a new optimal level. Assume also that the impact of the shock on consumption is permanent. In this case, the discounted sum of future consumption responses to the shock is positive. Provided that γ is bigger than 1 and the contemporaneous impact of the shock on consumption growth is negligible or non-negative, (12) implies that the shock lowers the SDF, and therefore, will have a positive risk premium. The bigger the impact of the shock on future consumption growth, the higher its risk premium.

3 News Shock Identification

Section 2 shows that the stochastic discount factor (SDF) is a function of fundamental shocks. To test this asset pricing model, we need to identify individual fundamental shocks. This section explains how we identify three technology shocks in a structural Vector Autoregression (VAR) analysis using the approach in Ben Zeev and Khan (2015).

For the discussion in this section, we assume that an econometrician who observes only the infinite sequence of observables, $\{z_{t-s}\}_{s=0}^{\infty}$, can correctly infer the state variables at time t, x_t. That is, the state space form (1) and (2) is invertible.[2] In this case, the information set of the econometrician is the same as that of the agent, $E\left[\cdot|\{z_{t-s}\}_{s=0}^{\infty}\right] = E\left[\cdot|\{x_{t-s}, z_{t-s}\}_{s=0}^{\infty}\right]$ (Fernández-Villaverde, Rubio-Ramírez, Sargent and Watson (2007)). Hence, the asset pricing model (13) can be solved using the expectation operator for the econometrician.

Following Ben Zeev and Khan (2015), we use the maximum forecast error variance (MFEV) approach proposed by Barsky and Sims (2011) to identify three technology shocks. The first two shocks are the TFP (total factor productivity) and IST (investment-specific technology) current shocks. The third shock is the IST news shock. In an economy where there are consumption goods and investment goods and where investment goods are produced from inputs of consumption goods, TFP measures the consumption good productivity and IST measures the transformation productivity of consumption into investment goods (Fisher (2006)). The TFP and IST current shocks are the traditional technology shocks which affect TFP and IST in the same period during which the shocks occur, respectively. In contrast, the IST news shock has no contemporaneous effect on IST but reflects anticipated changes in the future IST.

The identification methodology of Ben Zeev and Khan (2015) is based on the assumption that the investment-specific technology process is driven only by the IST current shock and IST news

[2]For further discussion on invertibilities, see Appendix A.2.

shock. An example of an IST process that satisfies this assumption is

$$log\left(IST_t\right) = \mu_{IST} + log\left(IST_{t-1}\right) + \varepsilon_{curr,t} + \varepsilon_{news,t-j}. \tag{14}$$

Here, IST_t is the level of investment-specific technology, $\varepsilon_{curr,t}$ is the IST current shock, and $\varepsilon_{news,t}$ is the IST news shock. Note that $\varepsilon_{news,t}$ does not affect the level of IST until time $t+j$. That is, $\varepsilon_{news,t}$ is the anticipated change in the j-period ahead IST level. The assumptions about the IST process and IST news shock imply that (i) any unanticipated change in IST is due to the IST current shock and that (ii) the two IST shocks should explain all variations in IST at all horizons. Therefore, in a VAR that includes TFP and IST as the first and second variables, the TFP and IST current shocks are identified from the first two elements of VAR residuals based on implication (i). The IST news shock is then identified as the shock that best explains the future movements of IST not accounted for by the two current shocks based on implication (ii).

The identification methodology of Ben Zeev and Khan (2015) and Barsky and Sims (2011) is based on a VAR system in levels. Estimating a VAR in levels produces consistent estimates of the VAR impulse responses even with cointegration of unknown form. Recall that z_t denotes the $k \times 1$ vector of observables in the state space form (1) and (2), and includes growth rates of non-cointegrated I(1) observables, error correction variables, and I(0) observables. Let y_t denote the $k \times 1$ vector of the corresponding observables in *log levels.*[3]

Since we assume that the state space form is invertible, the infinite order VAR innovations of z_t span the space of fundamental shocks. This in turn implies that the infinite order VAR innovations of y_t also span the space of fundamental shocks (see Watson (1994), chapter 3.2):

$$\begin{aligned} y_t &= P\left(L\right)y_{t-1} + u_t = P_1 y_{t-1} + P_2 y_{t-2} + \cdots + u_t \\ u_t &= A_0 \varepsilon_t. \end{aligned} \tag{15}$$

Here, $P\left(L\right)$ and A_0 are implicit functions of G, H, U, and V in the state space form of (1) and (2). Also, u_t is the vector of VAR reduced form innovations, and ε_t is the vector of fundamental shocks. To recover ε_t from u_t, we need to find the impact matrix, A_0. This matrix must satisfy

$$A_0 A_0' = \Sigma, \tag{16}$$

where Σ is the variance-covariance matrix of reduced form innovations. Let $\tilde{A}_0$ be the (lower-

[3]For example, suppose that the observables of interest are log consumption and log corporate earnings denoted by c_t and e_t, respectively. Further, assume that c_t and e_t are both I(1) and cointegrated, and the cointegration vector is $[1, -1]$. Then, z_t is

$$z_t = \begin{bmatrix} \Delta c_t \\ e_t - c_t \end{bmatrix},$$

and the corresponding y_t is

$$y_t = \begin{bmatrix} c_t \\ e_t \end{bmatrix}.$$

triangular) Cholesky decomposition of Σ:

$$\tilde{A}_0 \tilde{A}_0' = \Sigma.$$

Then, the set of A_0 that satisfies condition (16) can be written as the set of $k \times k$ orthonormal matrices of D:

$$\left\{A_0 : A_0 A_0' = \Sigma\right\} = \left\{\tilde{A}_0 D : DD' = I_k\right\}.$$

Therefore, if we identify D_i, the i-th column of D matrix, we can estimate the i-th fundamental shock from the reduced form innovations:

$$\varepsilon_{i,t} = \mathbf{e}_i A_0^{-1} u_t = \left(\mathbf{e}_i D^{-1}\right) \tilde{A}_0^{-1} u_t = D_i' \tilde{A}_0^{-1} u_t,$$

where $\mathbf{e}_i$ is the $k \times 1$ selection vector with one in the i-th place and zeros elsewhere.

We include TFP and IST as the first and second variables in y_t, and index the TFP and IST current shocks as the first and second fundamental shocks and the IST news shock as the third fundamental shock in the vector of ε_t. Since only the current shocks affect TFP and IST in the current period, they can be identified as the reduced form innovations in TFP and IST. Specifically, following Ben Zeev and Khan (2015), we identify the TFP current shock as the VAR innovation in TFP and the IST current shock as the innovation in IST orthogonalized with respect to the TFP current shock. Therefore,

$$D_1 = [1, 0, 0, \cdots, 0]'$$
$$D_2 = [0, 1, 0, \cdots, 0]',$$

and all the other columns of D have zeros in the first two elements:

$$D_i(1) = D_i(2) = 0 \quad \forall i \geq 3. \tag{17}$$

Note that D_1 and D_2 are orthogonal to all D_i for $i \geq 3$:

$$D_1' D_i = 0 \quad \forall i \geq 3$$
$$D_2' D_i = 0 \quad \forall i \geq 3.$$

Recall that the two IST technology shocks should explain all variations in IST at all horizons. Therefore, Ben Zeev and Khan (2015) identify the third column of D such that the forecast error variance of IST attributable to the IST news shock is maximized over horizon 0 to H periods under the constraint (17). Appendix A.1 shows that the solution to this maximization problem is the eigenvector associated with the largest eigenvalue of the lower-right $(k-2) \times (k-2)$ submatrix of

$\left[\sum_{h=0}^{H}\sum_{\tau=0}^{h}\frac{\left(B_{2,\tau}\tilde{A}_0\right)'\left(B_{2,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h}B_{2,\tau}\Sigma B_{2,\tau}'}\right]$, where B_τ is a function of of $P_1, \cdots, P_\tau$. In the words of Barsky and Sims (2011), "This procedure essentially identifies the news shock as the first principal component of observed technology orthogonalized with respect to its own innovation."

4 Data

We include eight variables in the VAR : TFP, IST, consumption, investment, output, hours, consumer confidence, and inflation. Technology measures of TFP and IST are crucial inputs when estimating technology shocks. Consumption, investment, output, and hours are the economic activities of interest. While we need only the consumption impulse responses to calculate the stochastic discount factor, we still include investment, output, and hours in the analysis for two reasons. First, including a sufficient number of state variables helps to reduce biases in the news shock estimation (see Appendix (A.2)). Second, these variables are the basic building blocks of most general equilibrium models. The impulse response functions of these variables tell us how a fundamental shock propagates through the system. The other two variables, consumer confidence and inflation, are forward looking variables. Including forward looking variables in the system helps with news shock identification (Barsky and Sims (2011); Sims (2012)). The empirical evidence suggests that consumer confidence contains fundamental information about future productivity growth over a relatively long horizon (Barsky and Sims (2011); Barsky and Sims (2012)). Inflation is commonly assumed to be forward looking in standard New Keynesian models and often included in the VAR for news shock identification (Ben Zeev and Khan (2015); Barsky and Sims (2011)).

Details on the VAR variables are as follows. The measure of TFP is a quarterly version of the Basu, Fernald and Kimball (2006) utilization-adjusted total factor productivity (TFP) series, downloaded from John Fernald's website (Fernald (2012)). The quarterly measure of IST is also from John Fernald's website, and defined by the relative price of non-equipment and non-durable goods and services to the price of equipment, software, and consumer durables.

The consumption series is the sum of non-durables and services. Following Justiniano, Primiceri and Tambalotti (2011) and Ben Zeev and Khan (2015), we define the investment series as the sum of private domestic investment and durable consumption. The output series is the non-farm business sector output. Consumption, investment, and output series are from the Bureau of Economic Analysis. Hours are non-farm business sector labor hours, downloaded from the Bureau of Labor Statistics. We convert consumption, investment, output, and hours to per capita terms by dividing them by the civilian non-institutionalized population aged sixteen and over. The population series is from the St. Louis Federal Reserve Bank website. Population series is observed monthly. To convert it to quarterly data, we take the last monthly observation from each quarter. Consumption, investment, and output are deflated using the corresponding 2009 chain-weighted deflators. Inflation is the percentage change in the non-durables and services deflator. Consumer confidence is series BUS5 (Business Conditions Expected During the Next 5 Years) from the Michigan Survey website. The quarterly consumer confidence data is available from 1960Q1, and the monthly consumer confidence data is available from 1978Jan. When the monthly consumer confidence data is not available, we use the quarterly consumer confidence data. When the monthly data is available, we use the last monthly consumer confidence index of each quarter.

All variables enter the VAR in log levels except for inflation and consumer confidence. We use four lags in the VAR and choose $H = 40$ as a truncation horizon, following Barsky and Sims (2011). Because consumer confidence data starts in 1960Q1, our sample period includes 220 quarters between 1960Q1 and 2015Q4.

The monthly stock data is from the Center for Research in Security Prices (CRSP). The book equity, sales, and operating income data is from Compustat. The three Fama and French (1992) factors, monthly risk-free rate, size and BM sorted portfolios, and the size and BM breakpoints are from Kenneth R. French's website.

5 Identification Results

In this section, we present the structural VAR identification results. The analysis shows that the IST news shock is an important source of business cycle fluctuations, induces significant long-run consumption risk, and accounts for 50% to 60% of consumption movements at medium and long horizons. It also shows that realized long-run consumption growth, frequently used as a measure for long-run consumption risk in existing literature, partially reflects IST news shock.

5.1 Impulse Responses

Figure 2 shows the impulse responses of the variables in the VAR to a positive one standard deviation IST news shock along with their 1st and 99th percentile Hall (2013) confidence bands. The confidence bands are calculated from 2,000 bootstrap replications of the reduced form VAR. Similarly to Ben Zeev and Khan (2015), we find that the IST news shock induces long-run growth in TFP, IST, consumption, investment, and output. Following a positive IST news shock, both TFP and IST rise gradually until they reach their new levels. The permanent increases in TFP and IST, which are measured as the impulse responses at quarter 40, are around 0.34% and 0.5%, respectively. Consumption jumps by 0.19% on impact and increases further. At its peak, consumption is 0.66% higher than it was before the shock. After the peak, consumption decreases slightly reaching a 0.56% response at quarter 40. Investment also jumps by 0.40% on impact and rises rapidly afterwards until it reaches a peak at quarter 5. At its peak, investment is 2.53% higher than it was before the shock. Investment then comes down over time to a level that is a little higher than its original level. Output also increases by 0.11% on impact and rises further to reach a 1.03% response at quarter 8. At quarter 40, output is 0.69% higher than it was before the shock. Hours does not respond on impact but starts to increase in quarter 1 until it reaches a 0.83% response at quarter 8. Then it decreases gradually and goes back to its original level by quarter 25. Consumer confidence jumps by 7.54 points and inflation drops by 0.15 percentage point on impact. These significant impact responses confirm that both consumer confidence and inflation contain information about future IST growth.

Figure 3 shows the impulse responses to a positive one standard deviation IST current shock. By construction, TFP is not affected by the IST current shock on impact. Over medium and long horizons, TFP is negatively affected by the IST current shock, although the effect is not significant. IST jumps up by 0.37% at quarter 0, further increases to 0.57% by quarter 3, and decreases gradually afterwards. The effect of the IST current shock on IST is not significant after quarter 30. A positive IST current shock induces long-run decline in economic activities. At quarter 40, consumption, investment, output, and hours are 0.95%, 1.63%, 1.08%, and 0.65% lower, respectively, than they were before the shock. These results are similar to the estimation results from Ben Zeev and Khan (2015). The IST current shock does not affect consumer confidence significantly at any horizon. On the other hand, it raises inflation by 0.10 percentage point on impact.

Figure 4 shows the impulse responses to a positive one standard deviation TFP current shock. By construction, a positive TFP current shock increases TFP by 0.66% on impact. However, this impact is transitory, and TFP decreases to its original level over time. The effect of the TFP current shock on IST is not significant at any horizon. The TFP current shock also generates temporary increases in consumption, investment, and output in the short run as well as a temporary decrease in hours. However, these effects quickly dissipate over medium horizons. Consumer confidence increases by 1.11 points on impact, but this movement is not significant. Inflation shows a hump-shaped response.

5.2 Forecast Error Variance Decomposition

Figure 5 displays the cumulative share of the forecast error variance attributable to the three technology shocks. Consistent with the impulse responses, each current shock explains a significant share of the forecast error variance of its corresponding technology measure over short horizons. However, the importance of current shocks decreases over time. At quarter 40, the IST news shock accounts for 37% and 72% of the forecast error variance of TFP and IST, respectively.

The IST news shock accounts for 25% of the forecast error variance of consumption at quarter 0 and more than 50% at quarter 4. At longer horizons, between 50% and 60% of consumption forecast error variance is attributable to the IST news shock. Although the current shocks explain a majority of technology movements at short horizons, they explain only a small share of consumption variance compared to the IST news shock. The share of the forecast error variance of consumption attributable to the IST current shock is 0.63% at quarter 0 and gradually increases to 17% at quarter 40. The share attributable to the TFP current shock is 2.1% at quarter 0 and less than 4% at all horizons.

Similar patterns are observed for other variables, too. Over medium and long horizons, the IST news shock explains about 60% of investment and output movements and 50% of hours fluctuations. On the other hand, the current shocks account for a much smaller share of forecast error variance. At quarter 40, the IST current shock explains 6%, 12%, and 20% of investment, output, and hours variances, respectively. The TFP current shock accounts for less than 4% of these variances. This result is consistent with the finding of Ben Zeev and Khan (2015) that IST news shocks explain a majority of business cycle fluctuations in macroeconomic aggregates. Lastly, it is worth pointing out that the IST news shock accounts for close to 70% of the forecast error variance of consumer confidence. This is consistent with the arguments of Barsky and Sims (2012), who find that news shock is an important source of variation in consumer confidence.

5.3 IST News Shock and the Stochastic Discount Factor

The identification results suggest that the IST news shock is a prominent source of long-run consumption risk among the IST news shock, IST current shock, and TFP current shock. In this section, we examine the consumption risks generated by these three technology shocks and their impacts on the stochastic discount factor (SDF) derived in Section 2.2.

Recall from (9) that the change in the log SDF following a shock can be expressed in terms of the changes in the future consumption growth due to the shock:

$$\begin{aligned} s_{t|t-1} - E_{t-1}\left[s_{t|t-1}\right] &= -\left[E_t - E_{t-1}\right](c_t - c_{t-1}) + (1-\gamma)\left[\left[E_t - E_{t-1}\right]\left(\sum_{h=0}^{\infty}\beta^h \Delta c_{t+h}\right)\right] \\ &= -\lambda_0' \varepsilon_t + (1-\gamma)\,\lambda(\beta)'\,\varepsilon_t. \end{aligned}$$

Therefore, we can calculate the unexpected change in the log SDF following a shock based on the corresponding consumption impulse response.

Table 1 calculates the change in short-run consumption growth, $[E_t - E_{t-1}](c_t - c_{t-1})$, and the change in long-run consumption growth, $[E_t - E_{t-1}]\left(\sum_{h=0}^{\infty}\beta^h \Delta c_{t+h}\right)$, following a positive one standard deviation IST news shock, IST current shock, and TFP current shock. We approximate the change in long-run consumption growth as the change in the discounted sum of expected consumption growth over the next 40 quarters, $[E_t - E_{t-1}]\left(\sum_{h=0}^{40}\beta^h \Delta c_{t+h}\right)$. This calculation assumes that we reach the limiting consumption response at or before 40 quarters. We assume that $\beta = 0.95^{\frac{1}{4}}$ following Malloy et al. (2009). The IST news shock has the biggest impact to both short-run and long-run consumption growth among the three technology shocks as it increases short-run consumption growth by 0.19% and long-run consumption growth by 0.56%. Both numbers are statistically significant. Note that the change in long-run consumption growth is almost three times bigger than the change in short-run consumption growth. The IST current shock does not significantly affect short-run consumption growth but lowers long-run consumption growth by 0.36%. The TFP current shock increases short-run consumption growth by 0.06%, but this effect is only marginally significant. It does not affect long-run consumption growth.

In order to understand how these technology shocks affect the SDF, let us assume that $\gamma = 10$, the risk aversion of top stockholders reported by Malloy et al. (2009). Ignoring changes in consumption growth that are not statistically significant, this assumption implies that the log SDF decreases by $(0.0019 + (10 - 1) \times 0.0056) = 0.0523$ upon an IST news shock, increases by $(10 - 1) \times 0.0036 = 0.0324$ upon an IST current shock, and does not move upon a TFP current shock. Therefore, the IST news shock has a positive risk premium, while the IST current shock has a negative risk premium. Also, the size of the risk premium on the IST news shock is about 1.6 times bigger than that on the IST current shock. This result indicates that IST news shocks are an important contributor to the risk premium of long-run consumption risk reported in the literature.

5.4 IST News Shock and Realized Long-Run Consumption Growth

Existing literature often uses realized long-run consumption growth, $\left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h}\right)$, as a proxy for the shock to expected long-run consumption growth, $[E_t - E_{t-1}] \left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h}\right)$ (Malloy et al. (2009); Parker and Julliard (2005); Boons (2016)). To understand how the technology shocks identified in this paper relate to the common measure for long-run consumption risk, we estimate predictive regressions of realized long-run consumption growth on the three technology shocks in Table 2. Realized long-run consumption growth for quarter t is calculated as the discounted sum of actual consumption growth over the next 16 quarters, $\left(\sum_{h=0}^{16} \beta^h \Delta c_{t+h}\right)$, as in the work of Malloy et al. (2009). We estimate the following regression:

$$\sum_{h=0}^{16} \beta^h \Delta c_{t+h} = \text{intercept} + \sum \text{coeff}_i \times \text{technology shock}_{i,t} + \text{error}_t.$$

In the left two columns, independent variables for quarter t are the four-quarter moving average technology shocks from quarter $t-3$ to quarter t. In the right two columns, independent variables for quarter t are technology shocks at quarter t.

The results in Table 2 show that the IST news shock has predictive power for realized long-run consumption growth. The coefficient estimate on the IST news shock is positive and statistically significant in all specifications. In the predictive regressions where the IST news shock is the only independent variable apart from a constant term, the moving-average IST news shock and current-quarter IST news shock explain 10.3% and 4.7% of realized long-run consumption growth, respectively, based on adjusted R^2. On the other hand, the IST and TFP current shocks do not have statistically significant coefficients, nor do they contribute to the adjusted R^2. Therefore, the existing measure for long-run consumption risk partially reflects IST news shocks, while it does not seem to reflect IST or TFP current shocks. This result further reinforces our main argument that IST news shocks are the most important fundamental source of long-run consumption risk reported in the literature.

6 The IST News Shock and Asset Prices

Since the IST news shock incurs persistent long-run consumption growth, it should carry a positive risk premium. In this section, we test the asset pricing model in Section 2.2 with the IST news shock as the main risk factor. We show that the IST news shock has a positive risk premium in the cross section of portfolios sorted on the IST news shock beta, BM, and size. We also find that firms with high IST news shock betas have high cash flow sensitivity with the IST news shock.

6.1 Portfolios Sorted on Technology Shock Betas

The analysis in Section 5 suggests that the IST news shock has a positive risk premium. To test this, we examine the properties of decile portfolios sorted on the IST news shock beta. To emphasize the importance of the IST news shock as a risk factor, we also look at decile portfolios sorted on the IST current shock beta and the TFP current shock beta.

We estimate pre-ranking IST news shock betas of individual stocks at each quarter by regressing their quarterly excess returns on the IST news shock in the previous 20 quarters. We then construct decile portfolios by sorting candidate stocks on the estimated pre-ranking IST news shock beta. We compute quarterly returns from monthly returns over the period of 1961Jan to 2015Dec using all available individual stocks from the CRSP universe. We apply the following filters: (i) we keep only ordinary common stocks by requiring the share code (SHRCD) to be 10 or 11; (ii) we impose the exchange code (EXCHCD) to be 1, 2, or 3 in order to select stocks traded at the NYSE, AMEX, or NASDAQ; (iii) we exclude stocks with negative or missing book equity, or stocks in the financial industry (SICCD 6000-6999) (Boons (2016)); and (iv) we keep a stock only for months in which its price is at least five dollars (Malloy et al. (2009)). Lastly, for a stock to be included in any decile portfolios over a given quarter, it should not have any missing returns over the previous 20 quarters. The characteristics of the decile portfolios are presented in Panel A of Table 3. We repeat the same analysis for the IST current shock and the TFP current shock in Panel B and C of Table 3, respectively.

First, we note that the post-ranking IST news shock betas are reasonably well aligned in the decile portfolios sorted on the pre-ranking IST news shock beta. However, this is not the case for the decile portfolios sorted on the pre-ranking IST or TFP current shock betas. This suggests that the betas of individual stocks with the IST and TFP current shocks are not persistent, reflecting the difficulty of accurately estimating time-varying sensitivities to technology shocks at the firm level (Papanikolaou (2010)).

Second, we observe a significant average return difference between the top decile portfolio (high IST news shock beta) and bottom decile portfolio (low IST news shock beta) in Panel A. The return difference is 5.4% per annum, with a t-statistic of 2.54. This sharp difference supports our argument that the IST news shock, as a source of long-run consumption risk, earns a positive risk premium in the cross section of stock returns. Even though the top three portfolios have higher standard deviations, their Sharpe ratios are still higher than those of the bottom three portfolios. In contrast, the return difference between the top and bottom decile portfolios is not significant for the portfolios sorted on either IST current shock beta (Panel B) or TFP current shock beta (Panel C). Since a positive IST current shock lowers future consumption growth as shown in Section 5, the long-run consumption risk hypothesis suggests that stocks with high IST current shock betas should earn lower returns. However, we are unable to confirm such an implication in Panel B because the pre-ranking beta sort fails to produce decile portfolios with increasing post-ranking betas for IST current shocks.

Lastly, we do not find any meaningful differences in the size and BM characteristics between the top and bottom IST news shock beta portfolios. We determine the size rank of a stock at each quarter, 1 for the smallest and 10 for the largest, using French's size breakpoints of the last month in the previous quarter. We measure the size rank score of a portfolio as the average size rank of its stocks, and we compute the BM ratio of a portfolio as the value-weighted BM ratio of its stocks. The size rank score of the top decile portfolio is 1.1 lower than that of the bottom decile portfolio. While this difference is statistically significant (t-statistic = 5.13), we do not consider the magnitude of the difference economically meaningful given that the size rank score is out of 1 to 10. Also, the difference in the BM ratio between the top and bottom decile portfolios is not statistically significant.

Overall, the findings in this section support our argument that the IST news shock is the main driver of the SDF. With this in mind, we focus on the IST news shock as the main risk factor in the asset pricing model of (12) and (13) in the following sections.

6.2 The IST News Shock and Cash Flow Growth

The previous section finds that firms with high IST news shock betas earn high expected returns. In this section, we show that firms with high IST news shock betas also have high cash flow sensitivity with the IST news shock.

The output impulse response in Figure 2 shows that a positive one standard deviation IST news shock increases aggregate output by 1% in the first three years following the shock. This evidence suggests that the IST news shock will also affect cash flows of individual firms. Specifically, we conjecture that firms with high IST news shock betas will experience higher cash flow growth than firms with low IST news shock betas upon a positive IST news shock. To test this, we estimate the following equation using the three-year cash flow growth of the decile portfolios sorted on IST news shock beta as the dependent variable:

$$\text{cash flow growth}_{p,(t,t+3)} = \text{intercept}_p + \sum \text{coeff}_p \times \text{IST news}_t + \text{error}_{p,t},$$

where p is the portfolio index. We use two measures for portfolio cash flow growth. The first measure is portfolio sales growth (Compustat item SALE), and the second measure is portfolio operating income growth (Compustat item OIBDP). In June of calendar year t, we calculate the future three-year sales and operating-income growth of a portfolio as the log growths of total real sales and operating income of firms in the portfolio between fiscal year $t-1$ and fiscal year $t+2$. The portfolio cash flow growth is then regressed on the previous four-quarter average IST news shock in June of calendar year t.

Table 4 reports the regression results for the top three and bottom three decile portfolios. The estimated coefficient on the IST news shock displays an increasing pattern from the 1st to 10th decile portfolio. For instance, the sales growth coefficient of the 1st decile portfolio is not statistically different from zero. On the other hand, the sales growth coefficient of the 10th decile portfolio is 0.094, with a t-statistic of 1.879. Similarly, the operating income growth coefficient of the 1st decile portfolio is not statistically different from zero, while that of the 10th decile portfolio is 0.095, with a t-statistic of 2.261. These differences in coefficients are statistically significant. Therefore, the cash flows of the top decile portfolio are more sensitive to the IST news shock than those of the bottom decile portfolio. Given that the IST news shock is a prominent source of long-run consumption risk, this result indicates that the cash flows of the top decile portfolio have higher long-run consumption risk than those of the bottom decile portfolio. Hence, the top decile portfolio earns higher expected returns partly because its cash flows have a higher IST news shock beta than the bottom decile portfolio. This result is consistent with the findings of Bansal, Dittmar and Lundblad (2005) who show that cash flow consumption beta, the projection coefficient of cash flow news onto consumption innovations, determines the cross-sectional risk premia of characteristic sorted portfolios.

Another interesting pattern in Table 4 is that the average cash flow growth increases with the portfolio decile. For example, the average three-year sales growth of the 1st decile portfolio is 0.103, while that of the 10th decile portfolio is 0.169. Likewise, the average three-year operating income growth of the 1st decile portfolio is 0.086, and that of the 10th decile portfolio is 0.208. These differences are statistically significant. Therefore, the cash flows of firms in the top decile portfolio grow faster than those in the bottom decile portfolio.

6.3 Asset Pricing Model with Consumption Residual Innovations

The result that portfolios with higher IST news shock betas earn higher expected returns suggests that the IST news shock is a priced risk factor in the cross section of asset returns. In the remaining sections, we formally test the asset pricing model of (12) and (13) with the IST news shock as the fundamental shock of interest. The asset pricing model requires that we include all shocks affecting consumption in the cross-sectional test. In this section, we explain how we control for the other shocks in our test.

Recall from Section 3 that the reduced form innovations of the VAR span the linear space of fundamental shocks and potential measurement errors. Therefore, we can identify the log stochastic discount factor (SDF) up to a linear transformation using the reduced form innovations. Since there are eight variables in the VAR, there are seven additional shocks orthogonal to the IST news shock. If all seven shocks are fundamental shocks that affect consumption, we need to include seven additional factors as well as the IST news shock in the SDF. However, if only a subset of those shocks drives consumption, including seven additional factors in the asset pricing test may result in an over-specification of the true model.

To determine how many additional factors to include in the asset pricing model, we apply the maximum forecast error variance (MFEV) approach from Section 3 to consumption and identify the principal components of residual consumption movements not accounted for by the IST news shock. Appendix A.3 shows that these principal components are linear transformations of the reduced form innovations orthogonal to the IST news shock which maximally contribute to consumption forecast error variance. Since the principal components explain the consumption movements not accounted for by the IST news shock, we call them consumption residual innovations.

Suppose that the first N (≤ 7) number of consumption residual innovations explain the consumption movements not accounted for by the IST news shock. Then the log SDF can be expressed in terms of the IST news shock, ε_{news}, and the N consumption residual innovations, ϵ_i for $i = 1, \cdots, N$:

$$\begin{aligned} s_{t|t-1} - E_{t-1}\left[s_{t|t-1}\right] &= -\left[E_t - E_{t-1}\right](c_t - c_{t-1}) + (1-\gamma)\left[\left[E_t - E_{t-1}\right]\left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h}\right)\right] \\ &= \left\{-b_{news}^{short} + (1-\gamma)\, b_{news}^{long}\right\} \varepsilon_{news,t} + \sum_{i=1}^{N} \left\{-b_i^{short} + (1-\gamma)\, b_i^{long}\right\} \epsilon_{i,t} \\ &= \left\{-b^{short} + (1-\gamma)\, b^{long}\right\}' f_t \\ &= b' f_t. \end{aligned} \tag{18}$$

Here, b_{news}^{short} and b_{news}^{long} represent the impact of a (positive one-standard deviation) IST news shock on the short-run consumption response, $[E_t - E_{t-1}](c_t - c_{t-1})$, and long-run consumption response, $[E_t - E_{t-1}]\left(\sum_{h=0}^{40} \beta^h \Delta c_{t+h}\right)$, respectively. Likewise, b_i^{short} and b_i^{long} represent the impact of the i-th consumption residual innovation on the consumption responses. Also, b^{short} is the vector of $\left[b_{news}^{short}\ b_1^{short} \cdots\ b_N^{short}\right]'$ and b^{long} is the vector of $\left[b_{news}^{long}\ b_1^{long} \cdots\ b_N^{long}\right]'$. Lastly, f_t is the vector of the IST news shock and consumption residual innovations, $[\varepsilon_{news,t}\ \epsilon_1 \cdots\ \epsilon_N]'$. For the derivation, see Appendix A.4.

Figure 6 shows the identification results of consumption residual innovations. The left graph displays the cumulative share of consumption forecast error variance attributable to the IST news shock and the first two consumption residual innovations, ϵ_1 and ϵ_2. Recall that the IST news shock accounts for 25% of consumption forecast error variance at quarter 0 and between 50% and 60% in long horizons. The first consumption residual innovation explains 54% of consumption forecast error variance at quarter 0, 50% at quarter 1, and between 35% and 45% in longer horizons. The second consumption residual innovation explains 19% at quarter 0 and less than 3% over horizons longer than two years. The three shocks together explain more than 96% of consumption forecast error variance at all horizons. This result indicates that there are possibly two more fundamental shocks affecting consumption in addition to the IST news shock.

The right graph shows the consumption impulse responses to the IST news shock and the two consumption residual innovations. Note that the impulse responses to consumption residual innovations are linear transformations of impulse responses to the true fundamental shocks (see Appendix A.4). Being the first principal component, the first consumption residual innovation generates the bigger consumption response than the second innovation at all horizons. The short-run and long-run consumption responses following the first consumption residual innovation are $b_1^{short} = 0.0028$ and $b_1^{long} = 0.0058$, respectively. For the second innovation, $b_2^{short} = -0.0016$ and $b_2^{long} = 0.0010$.

In summary, the analysis in this section suggests that the IST news shock and the first two consumption residual innovations are sufficient to fully specify the SDF. As such, our baseline asset pricing model includes these three shocks as the risk factors in the SDF.

6.4 Euler Equation Estimation for Portfolios Sorted on IST News Shock Beta

In this section, we estimate the risk aversion parameter γ and test the asset pricing model of (12) and (13) using the 10 portfolios sorted on IST news shock beta. The log stochastic discount factor (SDF) is specified by (18). Let R_t^e the 10×1 vector of portfolio excess returns in quarter t. Following Parker and Julliard (2005) and Malloy et al. (2009), we estimate the Euler equations via GMM with a pre-specified weighting matrix. The empirical moment function is

$$g\left(R_t^e, S_{t|t-1}; \alpha, \gamma, \mu\right) = \begin{bmatrix} R_t^e - \alpha \mathbf{1}_{10} + R_t^e \left(\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]} - \mu \right) \\ \frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]} - \mu \end{bmatrix},$$

where

$$\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]} = exp\left[b' f_t - \frac{1}{2}|b|^2\right].$$

Also, $\mathbf{1}_{10}$ is a 10×1 vector of ones, α is the intercept of the Euler equation, γ is the risk aversion parameter, and μ is the mean of the normalized SDF, $S_{t|t-1}/E_{t-1}\left[S_{t|t-1}\right]$.[4] The weighting matrix is an identity matrix.

Table 5 reports the Euler equation estimation results. In Panel A, we estimate the unrestricted moment conditions. In Panel B, we estimate the moment conditions with the restriction $\alpha = 0$. The first column reports the estimation results of Model 1, our baseline model. As discussed in the previous section, the baseline model includes the IST news shock and the first two consumption residual innovations in the SDF. The estimated γ is positive and statistically significant. It is 92 with

[4] Because f_t has a sample mean 0 over the period from 1961Q4 to 2015Q4 by construction, the normalized SDF has a sample mean 1 over the same period. However, the portfolio returns span a smaller period from 1966Q1 to 2015Q4. Therefore, we estimate the mean of the normalized SDF over the smaller sample period using GMM. See Appendix C in Malloy et al. (2009).

a t-statistic 1.99 for the unrestricted case and 80 with a t-statistic 2.24 for the restricted case. This indicates that a shock that increases long-run consumption growth earns a positive risk premium. Also, the intercept α in the unrestricted case is close to 0 and not statistically significant. The J-test fails to reject the null hypothesis that the pricing errors are jointly 0 across the 10 portfolios in both the unrestricted and restricted cases. Therefore, the model successfully prices the 10 portfolios.

The risk aversion estimates of Model 1 are relatively high compared to the estimates reported in the literature. For example, Parker and Julliard (2005) report that the risk aversion implied by the 25 Fama and French (1992) portfolio returns and long-run aggregate non-durable consumption growth ranges from 9.1 to 39.4. Malloy et al. (2009) find that the risk aversion needs to be around 46 to match the 25 portfolio average returns using long-run aggregate non-durable consumption growth. One reason might be the difference in consumption measure. We measure consumption as aggregate non-durable and service consumption, as opposed to aggregate non-durable consumption. If nondurable consumption has more volatile long-run growth than nondurable and service consumption, this will make our risk aversion estimate higher. Another reason for the higher risk aversion might be the non-invertibility problem. In general, structural VAR analysis with news shocks has non-invertibilities (see Appendix A.2). When there is a non-invertibility in the state space representation, the structural VAR analysis identifies shocks with errors. The errors in the IST news shock will bias the return covariance with the SDF downward, and this bias is likely to be bigger for top decile portfolios. Therefore, the covariance difference between top and bottom decile portfolios will be biased downward and the estimated risk premium and the implied risk aversion will be biased upward.

To understand the relative importance of the IST news shock and the consumption residual innovations in the cross section, we also consider Model 2 and Model 3 in the next two columns. Model 2 assumes that the SDF includes the IST news shock and the first consumption residual innovation. Model 3 assumes that the SDF is determined by the IST news shock only. Model 2 has similar estimation results to Model 1. Because the second consumption residual innovation has a small effect on consumption, it contributes little to the SDF. Therefore, removing it from the SDF does not significantly alter the estimation result. On the other hand, removing both residual innovations from the stochastic discount factor results in a much higher risk aversion estimate. The estimated γ of Model 3 is 130 with a t-statistic 2.2 for the unrestricted case and 118 with a t-statistic 2.5 for the restricted case. Without the consumption residual innovations, Model 3 attributes all risk premia to the IST news shock, making the risk aversion estimate higher. Still, Model 3 has R^2's that are comparable to those of Model 1, and the J-test indicates that Model 3 successfully prices the 10 portfolios. This suggests that the IST news shock is the more important risk factor than the two consumption residual innovations in the cross section of the 10 portfolios.

6.5 Cross-Sectional Tests of the Linear Factor Model

In this section, we test the asset pricing implications of the IST news shock in the cross section of portfolio returns by approximating the model (12) and (13) as a linear factor model. The linear factor model has an advantage in that it can estimate the risk premia of individual risk factors. This means that we can test whether the IST news shock is priced in the cross section separately from other risk factors, such as consumption residual innovations, through the linear factor model. Also, since linear factor models are widely used, we can easily compare the results of our asset pricing model to the existing findings in the literature. As test assets, we use decile portfolios sorted by size and book-to-market, as studies report that these characteristics are related to long-run consumption risk (Parker and Julliard (2005); Malloy et al. (2009); Xiao et al. (2013)). We also include decile portfolios sorted on IST news shock beta in the test assets because the IST news shock is our main risk factor of interest.[5]

Using the results in Section 6.3, Appendix A.5 shows that the asset pricing model of (13) with (12) can be approximated as a linear factor model with three shocks, the IST news shock and the first two consumption residual innovations, which are shown to capture more than 95% of consumption dynamics in Section 6.3 :

$$\begin{aligned} E\left[R_{i,t}-R_{f,t}\right] =& b_{news} Cov\left(\varepsilon_{news,t}, R_{i,t}-R_{f,t}\right) \\ &+ b_1 Cov\left(\epsilon_{1,t}, R_{i,t}-R_{f,t}\right) + b_2 Cov\left(\epsilon_{2,t}, R_{i,t}-R_{f,t}\right), \end{aligned} \tag{19}$$

where b_{news}, b_1, and b_2 are implicit functions of parameters in the economy. Our main interest is in whether the first term on the RHS in (19) meaningfully explains the cross section of our test portfolio returns. To test this, we consider the following return generating process with the IST news shock:

$$Model\ 1: \ R_{p,t}-R_{f,t} = a_{M1,p} + \beta_{news,p}\varepsilon_{news,t} + \beta_{\epsilon_1,p}\epsilon_{1,t} + \beta_{\epsilon_2,p}\epsilon_{2,t} + e_{M1,p,t}$$

where p is an index for the thirty test portfolios. Model 1 is implied by our baseline asset pricing model. To check the robustness of the risk premium on the IST news shock, we also consider the

[5] While portfolios sorted on past returns (momentum) are frequently considered in cross-sectional asset pricing tests, we do not consider those portfolios because (i) momentum returns are well explained by earnings surprises which may not be directly related to the news about future productivity (Chordia and Shivakumar (2006); Novy-Marx (2015)), and (ii) momentum returns are shown to be attributable to the shocks to current consumption rather than future consumption (Xiao et al. (2013)).

following return generating processes :

$$
\begin{aligned}
Model\ 2: \ & R_{p,t} - R_{f,t} = a_{M2,p} + \beta_{news,p}\varepsilon_{news,t} + \beta_{\epsilon_1,p}\epsilon_{1,t} + e_{M2,p,t} \\
Model\ 3: \ & R_{p,t} - R_{f,t} = a_{M3,p} + \beta_{news,p}\varepsilon_{news,t} + e_{M3,p,t} \\
Model\ 4: \ & R_{p,t} - R_{f,t} = a_{M4,p} + \beta_{news,p}\varepsilon_{news,t} + \beta^{IST}_{curr,p}\varepsilon^{IST}_{curr,t} + \beta^{TFP}_{curr,p}\varepsilon^{TFP}_{curr,t} + e_{M4,p,t} \\
Model\ 5: \ & R_{p,t} - R_{f,t} = a_{M5,p} + \beta_{news,p}\varepsilon_{news,t} + \beta_{mkt,p}\left(R_{mkt,t} - R_{f,t}\right) + e_{M5,p,t}.
\end{aligned}
$$

To see the effect of consumption residual innovations on the risk premium on the IST news shock, we drop $\epsilon_{2,t}$ and $(\epsilon_{1,t}, \epsilon_{2,t})$ in Model 2 and Model 3, respectively. We also test an asset pricing model with the three technology shocks, the IST news shock, the IST current shock, and the TFP current shock, together in Model 4. Lastly, the effect of the inclusion of the aggregate market is considered in Model 5.

Panel A of Table 6 reports the cross-sectional test results using the two-pass methodology by Fama and MacBeth (1973) with the adjustment of Shanken (1992). Across all specifications, the clear message is that the IST news shock carries a significant risk premium in the cross section of the 30 portfolios. The t-statistic for the premium on the IST news shock beta is statistically significant in four out of the five models at a 5% significance level (except for Model 4, where the premium is significant at a 10% significance level).

Another important finding is that the IST news shock has the biggest contribution to the cross-sectional *Adj-*R^2's across the five models. The result of Model 3 shows that the single factor model with the IST news shock can explain about 60% of the cross-sectional variation in the average returns. Additional factors contribute less than 10% to the *Adj-*R^2 in other models. The fitted returns of Model 1 and 3 are plotted in the top two graphs of Figure 7. Note also that when we consider two factors of the IST news shock and market excess return in Model 5, the IST news shock beta has a significant risk premium while market beta does not. This is an interesting result given that the recursive preferences of Epstein and Zin (1989) imply that the return on the aggregate wealth portfolio in the economy, reflecting long-run consumption growth, should be a risk factor.

For benchmark asset pricing models, we consider the CAPM and Fama-French three factor model. Results are reported in Panel B of Table 6 and the bottom two graphs of Figure 7. The CAPM does not explain the cross section of returns well compared to our baseline model. The *Adj-*R^2 of CAPM is only 44.3%, which is substantially lower than 62.3%, the *Adj-*R^2 of our baseline model (Model 1), or 60.9%, the *Adj-*R^2 of the single factor model with the IST news shock (Model 3). As well documented in the literature, the Fama-French three factor model explains the cross-sectional variation in returns very well, achieving 80.2% of the *Adj-*R^2. Considering that decile portfolios sorted by size or book-to-market are inherently related to the three factor model, such a high *Adj-*R^2 is not surprising. However, the three factor model performs worse than other models in the context of mean absolute pricing error (MAPE). The MAPE of the Fama-French three factor model is 1.2% per quarter, which is more than twice the MAPE of any other model. This is due to the fact that decile portfolios sorted on IST news shock beta are not explained by the three factor model. In the 10 portfolios sorted on IST news shock beta, the MAPE of the Fama-French three factor model rises to 3% per quarter.

In summary, we find strong evidence that investors require a risk premium for the IST news shock in the cross section of stock returns.

7 Conclusion

Existing studies on long-run risk point to common exogenous causes underlying related empirical regularities. Findings in these studies suggest that these common fundamental causes generate long-run consumption risk, drive business cycles, affect firm cash flows, and contribute to equity risk premium. In this paper, we propose that news about future investment-specific technology (IST) is one such fundamental shock. IST news shocks refer to predicted, but not yet materialized, technological improvements in the production of investment goods such as computers, machines, and heavy equipment. The literature investigating macroeconomic dynamics suggests that IST news shocks are an important source of business cycle fluctuations.

We identify the IST news shock using a structural VAR analysis and show that it is a prominent source of long-run consumption risk. A positive one standard deviation IST news shock increases consumption by 0.56% over a 10 year horizon. Also, between 50% and 60% of consumption forecast error variance is attributable to IST news shock at 2 to 10 year horizons.

We use the identified IST news shock as a risk factor in the asset pricing model of our economy where the representative agent cares about the prospects of her future consumption. The stochastic discount factor (SDF) is a function of fundamental shocks, and the effect of a fundamental shock on the SDF can be expressed in terms of changes in long-run consumption growth due to the shock. As the IST news shock induces significant long-run consumption growth, investors in our economy require a positive risk premium on the IST news shock.

Consistent with this implication, we find that the IST news shock carries a significant risk premium in the cross section of stock returns. Firms with high IST news shock betas tend to have higher returns on average than firms with low betas. We also find that the IST news shock affects stock returns through the channel of expected cash flow growth. The cash flows of firms with high IST news shock betas are more sensitive to the IST news shock than those with low betas.

Our results suggest that investigating the effect of fundamental shocks in asset prices can provide valuable insights on the common sources of various empirical patterns. In all, our empirical evidence shows that macroeconomic shocks are more closely linked to asset prices than they appear to be and can provide a guidance on differentiating risk-based reward from friction-driven mispricing.

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A Appendix

A.1 Identification Strategy for the IST News Shock

We explain IST news shock identification methodology in detail. This method was first proposed by Barsky and Sims (2011) for TFP news shock identification and was extended by Ben Zeev and Khan (2015) for IST news shock identification.

The $k \times 1$ vector of observables y_t follow a VAR in log levels :

$$\begin{aligned} y_t &= P(L)\, y_{t-1} + u_t = P_1 y_{t-1} + P_2 y_{t-2} + \cdots + u_t \\ u_t &= A_0 \varepsilon_t. \end{aligned} \tag{20}$$

Here, u_t is the vector of reduced form innovations and ε_t is the vector of fundamental shocks. We assume that ε_t is conditionally normal and homoskedastic, and satisfies $E_{t-1}[\varepsilon_t] = \mathbf{0}_k$, $E_{t-1}[\varepsilon_t \varepsilon_t'] = I_k$, $E_{t-1}\left[\varepsilon_{t+s}\varepsilon_{t+h}'\right] = \mathbf{0}_{k\times k}$ for $s \neq h$, where $\mathbf{0}_k$ is an $k \times 1$ vector of zeros, I_k is an k-dimensional identity matrix, and $\mathbf{0}_{k\times k}$ is an $k \times k$ matrix of zeros. . To identify ε_t from u_t, we need to find the impact matrix, A_0. This matrix must satisfy

$$A_0 A_0' = \Sigma, \tag{21}$$

where Σ is the variance-covariance matrix of reduced form innovations. Let $\tilde{A}_0$ the (lower-triangular) Cholesky decomposition of Σ :

$$\tilde{A}_0 \tilde{A}_0' = \Sigma.$$

Then, the set of A_0 that satisfies condition (21) can be written as the set of $k \times k$ orthonormal matrices of D :

$$\left\{A_0 : A_0 A_0' = \Sigma\right\} = \left\{\tilde{A}_0 D : DD' = I_k\right\}.$$

Therefore, if we identify D_i, the i-th column of D matrix, we can estimate the i-th fundamental shock from the reduced form innovations :

$$\varepsilon_{i,t} = \mathbf{e}_i A_0^{-1} u_t = \left(\mathbf{e}_i D^{-1}\right) \tilde{A}_0^{-1} u_t = D_i' \tilde{A}_0^{-1} u_t,$$

where $\mathbf{e}_i$ is the $k \times 1$ selection vector with one in the i-th place and zeros elsewhere.

We include TFP and IST as the first and second variables in y_t, and index TFP and IST current shocks as the first and second fundamental shocks and IST news shock as the third fundamental shock in the vector of ε_t. Since only the current shocks affect TFP and IST at the current period, they can be identified as the reduced form innovations in TFP and IST. Specifically, following Ben Zeev and Khan (2015), we identify the TFP current shock as the VAR innovation in TFP and IST current shock as the innovation in IST orthogonalized with respect to the TFP current shock.

Therefore,

$$D_1 = [1, 0, 0, \cdots, 0]'$$
$$D_2 = [0, 1, 0, \cdots, 0]'$$

and all the other columns of D have zeros in the first two elements :

$$D_j(1) = D_j(2) = 0 \quad \forall j \geq 3. \tag{22}$$

Note that D_1 and D_2 are orthogonal to all D_j for $j \geq 3$:

$$D_1' D_j = 0 \quad \forall j \geq 3$$
$$D_2' D_j = 0 \quad \forall j \geq 3.$$

Recall that the two IST technology shocks should explain all variations in IST at all horizons. Therefore, the third column of D is identified such that the forecast error variance of IST attributable to the IST news shock is maximized over horizon 0 to H periods under the constraint (22). From (20), the h-step ahead forecast error of y_t is a linear function of $u_t, u_{t+1}, \cdots, u_{t+h}$:

$$\begin{aligned} y_{t+h} - E_{y,t-1}[y_{t+h}] &= y_{t+h} - E_{t-1}[y_{t+h}] \\ &= \sum_{\tau=0}^{h} B_{h-\tau} u_{t+\tau} = \sum_{\tau=0}^{h} B_{h-\tau} \tilde{A}_0 D \varepsilon_{t+\tau}, \end{aligned}$$

where $B_{h-\tau}$ is a function of of $P_1, \cdots, P_{h-\tau}$. Therefore, the τ-step ahead forecast error variance of variable i attributable to the time-t fundamental shock j is

$$\begin{aligned} \sigma_{i,j}^2(\tau) &= \mathbf{e}_i' \left(B_\tau \tilde{A}_0 D \mathbf{e}_j \mathbf{e}_j' D' \tilde{A}_0' B_\tau' \right) \mathbf{e}_i \\ &= B_{i,\tau} \tilde{A}_0 D_j D_j' \tilde{A}_0' B_{i,\tau}', \end{aligned}$$

where, $\mathbf{e}_i$ is a vector with one in the i-th place and zeros elsewhere, $B_{i,\tau}$ is the i-th row of $k \times k$ matrix B_τ, and D_j is the j-th column of D.

Let $\sigma_i^2(\tau)$ the total τ-step ahead forecast error variance of variable i attributable to time-t shocks :

$$\begin{aligned} \sigma_i^2(\tau) &= \sum_{j=1}^{k} \sigma_{i,j}^2(\tau) \\ &= B_{i,\tau} \Sigma B_{i,\tau}'. \end{aligned}$$

The total share of the forecast error variance of variable i attributable to fundamental shock j at horizon h is then

$$\begin{aligned}\Omega_{i,j}(h) &= \frac{\mathbf{e}_i'\left(\sum_{\tau=0}^{h} B_\tau \tilde{A}_0 D \mathbf{e}_j \mathbf{e}_j' D' \tilde{A}_0' B_\tau'\right)\mathbf{e}_i}{\mathbf{e}_i'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau'\right)\mathbf{e}_i} \\ &= \frac{\sum_{\tau=0}^{h} B_{i,\tau} \tilde{A}_0 D_j D_j' \tilde{A}_0' B_{i,\tau}'}{\sum_{\tau=0}^{h} B_{i,\tau} \Sigma B_{i,\tau}'} \\ &= \frac{\Sigma_{\tau=0}^{h} \sigma_{i,j}^2(\tau)}{\Sigma_{\tau=0}^{h} \sigma_i^2(\tau)}.\end{aligned}$$

Since the IST current shock and the IST news shock account for all variations in IST at all horizons, we have

$$\sigma_{2,2}^2(\tau) + \sigma_{2,3}^2(\tau) = \sigma_2^2(\tau) \quad \forall \tau.$$

Therefore,

$$\sum_{\tau=0}^{h}\left\{\sigma_{2,2}^2(\tau) + \sigma_{2,3}^2(\tau)\right\} = \sum_{\tau=0}^{h} \sigma_2^2(\tau) \quad \forall h.$$

Dividing both sides by $\sum_{\tau=0}^{h} \sigma_2^2(\tau)$ leads to :

$$\Omega_{2,2}(h) + \Omega_{2,3}(h) = 1 \quad \forall h. \tag{23}$$

Since D_2 have already been identified, $\Omega_{2,2}$ is fixed. Therefore, we choose D_3 such that (23) holds as closely as possible. Note that

$$\Omega_{2,2}(h) + \Omega_{2,3}(h) \leq \sum_{j=1}^{k} \Omega_{2,j}(h) = 1 \quad \forall h,$$

by definition of forecast error variance. Hence, making (23) hold as closely as possible is equivalent to maximizing $\Omega_{2,3}(h)$ over different horizons. Specifically, Ben Zeev and Khan (2015) suggest the following optimization problem :

$$\begin{aligned} D_3^* &= \arg\max_{D_3} \sum_{h=0}^{H} \Omega_{2,3}(h) \\ &= \arg\max_{D_3} \sum_{h=0}^{H} \frac{\sum_{\tau=0}^{h} B_{2,\tau} \tilde{A}_0 D_3 D_3' \tilde{A}_0' B_{2,\tau}'}{\sum_{\tau=0}^{h} B_{2,\tau} \Sigma B_{2,\tau}'} \\ s.t. \quad & D_3(1) = D_3(2) = 0 \\ & D_3' D_3 = 1. \end{aligned} \tag{24}$$

The first constraint ensures that D_3^* is orthogonal to D_1 and D_2. The last constraint ensures that

D_3^* is a column of an orthonormal matrix.

Uhlig (2003) shows that the maximization problem (24) can be rewritten as,

$$\begin{aligned} D_3^* &= \arg\max_{D_3} \left\{ D_3' \left[\sum_{h=0}^{H} \sum_{\tau=0}^{h} \frac{\left(B_{2,\tau}\tilde{A}_0\right)' \left(B_{2,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h} B_{2,\tau}\Sigma B_{2,\tau}'} \right] D_3 \right\} \\ s.t. \quad & D_3(1) = D_3(2) = 0 \\ & D_3' D_3 = 1. \end{aligned}$$

Therefore, the lower $(k-2)\times 1$ subvector of D_3^* is the eigenvector associated with the largest eigenvalue of the lower-right $(k-2)\times(k-2)$ submatrix of $\left[\sum_{h=0}^{H}\sum_{\tau=0}^{h} \frac{\left(B_{2,\tau}\tilde{A}_0\right)'\left(B_{2,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h} B_{2,\tau}\Sigma B_{2,\tau}'}\right]$.

A.2 Non-invertibility

In this section, we briefly discuss the invertibility assumption. For convenience, we repeat the state space form (1) and (2) below :

$$\begin{aligned} x_t &= Gx_{t-1} + H\varepsilon_t \\ z_t &= Ux_{t-1} + V\varepsilon_t. \end{aligned}$$

The innovations from a VAR in the observables can be expressed as

$$z_t - E_{z,t-1}[z_t] = U\left(x_{t-1} - E_{z,t-1}[x_{t-1}]\right) + V\varepsilon_t.$$

When some of the state variables are not observable or cannot be inferred from the observables, the econometrician's information set is smaller than the agents' information set.[6] In that case, $E_{z,t-1}[x_{t-1}] \neq x_{t-1}$ and a structural VAR analysis identifies ε_t with errors Sims (2012).

A model with anticipated shocks to future state variables, such as news shocks, often has a non-invertibility problem. As an illustration, suppose that the the IST process is defined as (14). Agents in this economy base their decisions not only on the current level of IST but also on the future level of IST. This implies that the time t state variables include the past IST news shocks which have not yet loaded onto the level of IST, namely $\varepsilon_{news,t-1}$, $\varepsilon_{news,t-2}$,$\cdots$, $\varepsilon_{news,t-(j-1)}$. Since an econometrician does not observe current shocks and news shocks separately, individual IST news shocks are not observable and the state space form is not invertible.

In terms of asset pricing tests, non-invertibility causes "errors in variables" problem. Suppose that the true IST news shock betas are positive across stocks. When the true betas are positive, the errors in the IST news shock cause the estimated betas to be biased downwards. Moreover,

[6] Fernández-Villaverde et al. (2007) discuss the condition on G, H, U, and V for a state space form to be invertible.

these biases are bigger for the stocks with higher (true) betas. In consequence, the estimated risk premium on the IST news shock is bigger than the true risk premium. Non-invertibilities also bias impulse responses of variables to the IST news shock. This means that the long-run consumption risk calculated from the consumption impulse response should be taken with a caution. These observations suggest that we need to be careful when applying the IST news shock estimated from the structural VAR analysis to asset pricing tests. Nevertheless, if the errors in the estimated IST news shock are relatively small, we will still get a reasonable range of risk premium on the IST news shock. Moreover, the qualitative results from the asset pricing test will still be consistent with the true effect of the IST news shock on asset returns.

Sims (2012) investigates how important non-invertibilities are in news shock identification. He provides simulation evidence that non-invertibility is not a major concern in practice. The Barsky and Sims (2011) structural VAR analysis captures the dynamics implied by the model pretty well and the biases in the estimated impulse responses to the news shock are very small. Also, the correlation between the true news shock and Barsky and Sims (2011) identified news shock is over 70% on average. These results indicate that the errors from imperfectly forecasting the state, $x_{t-1} - E_{y,t-1}[x_{t-1}]$, are quite small.

A.3 Identification Strategy for Consumption Residual Innovations

In this section, we apply the maximum forecast error variance (MFEV) approach from Section 3 to consumption forecast error variance to find two consumption residual innovations.

We identify the first consumption residual innovation as the linear transformation of the reduced form innovations which best explains consumption movements subject to the constraint that it is orthogonal to the IST news shock. Let the first residual innovation be ϵ_1. Let D_3^* denote the identification vector associated with the IST news shock, $\varepsilon_{news,t} = D_3^* \tilde{A}_0^{-1} u_t$. We compute $\epsilon_{1,t}$ as

$$\epsilon_{1,t} = D_{c1}^{*\prime} \tilde{A}_0^{-1} u_t,$$

where u_t is the reduced form innovations, $\tilde{A}_0$ is the lower triangular Cholesky decomposition of the variance-covariance matrix of the reduced form innovations, and D_{c1}^* is the solution to the maximization problem

$$\begin{aligned} D_{c1}^* &= \arg\max_{D_{c1}} \sum_{h=0}^{H} \Omega_{3,c1}(h) \\ &= \arg\max_{D_{c1}} \sum_{h=0}^{H} \frac{\sum_{\tau=0}^{h} B_{3,\tau} \tilde{A}_0 D_{c1} D_{c1}' \tilde{A}_0' B_{3,\tau}'}{\sum_{\tau=0}^{h} B_{3,\tau} \Sigma B_{3,\tau}'} \qquad (25) \\ s.t. \quad & D_{c1}' D_3^* = 0 \\ & D_{c1}' D_{c1} = 1. \end{aligned}$$

Here, $\Omega_{3,c1}(h)$ is the total share of the forecast error variance of consumption (3rd variable in the VAR) attributable to $\epsilon_{1,t}\left(= D_{c1}' \tilde{A}_0^{-1} u_t\right)$ at horizon h.

The maximization problem (25) can be rewritten as,

$$
\begin{aligned}
D_{c1}^* &= \arg\max_{D_{c1}} \left\{ D_{c1}' \left[\sum_{h=0}^{H} \sum_{\tau=0}^{h} \frac{\left(B_{3,\tau}\tilde{A}_0\right)' \left(B_{3,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h} B_{3,\tau} \Sigma B_{3,\tau}'} \right] D_{c1} \right\} \\
s.t. \quad & D_{c1}' D_3^* = 0 \\
& D_{c1}' D_{c1} = 1.
\end{aligned}
$$

Let $N(D_3^*)$ the $k \times (k-1)$ orthonormal basis for the null space of D_3^* :

$$
\begin{aligned}
N(D_3^*)' N(D_3^*) &= I_{k-1} \\
N(D_3^*)' D_3^* &= \mathbf{0}_{k-1}.
\end{aligned}
$$

Then, the constraints $D_{c1}' D_3^* = 0$ and $D_{c1}' D_{c1} = 1$ imply that D_{c1} is expressed as $D_{c1} = N(D_3^*) j_{c1}$ for a $(k-1) \times 1$ vector of j_{c1} with $j_{c1}' j_{c1} = 1$. Therefore, we can rewrite the maximization problem as

$$
\begin{aligned}
j_{c1}^* &= \arg\max_{j_{c1}} \left\{ j_{c1}' N(D_3^*)' \left[\sum_{h=0}^{H} \sum_{\tau=0}^{h} \frac{\left(B_{3,\tau}\tilde{A}_0\right)' \left(B_{3,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h} B_{3,\tau} \Sigma B_{3,\tau}'} \right] N(D_3^*) j_{c1} \right\} \\
s.t. \quad & j_{c1}' j_{c1} = 1.
\end{aligned}
$$

Calculation shows that j_{c1}^* is the $(k-1) \times 1$ eigenvector associated with the largest eigenvalue of the matrix,

$$
N(D_3^*)' \left[\sum_{h=0}^{H} \sum_{\tau=0}^{h} \frac{\left(B_{3,\tau}\tilde{A}_0\right)' \left(B_{3,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h} B_{3,\tau} \Sigma B_{3,\tau}'} \right] N(D_3^*). \tag{26}
$$

Next, we find the second consumption residual innovation ϵ_2 as the linear transformation of the reduced form innovations which best explains consumption movements subject to the constraint that it is orthogonal to the IST news shock and the first consumption residual innovation ϵ_1 :

$$
\epsilon_{2,t} = D_{c2}^{*\prime} \tilde{A}_0^{-1} u_t,
$$

where

$$D_{c2}^* = \arg\max_{D_{c2}} \left\{ D_{c2}' \left[\sum_{h=0}^{H} \sum_{\tau=0}^{h} \frac{\left(B_{3,\tau}\tilde{A}_0\right)' \left(B_{3,\tau}\tilde{A}_0\right)}{\sum_{\tau=0}^{h} B_{3,\tau}\Sigma B_{3,\tau}'} \right] D_{c2} \right\}$$

$$\begin{aligned} s.t. \quad & D_{c2}' D_3^* = 0 \\ & D_{c2}' D_{c1}^* = 0 \\ & D_{c2}' D_{c2} = 1. \end{aligned}$$

Following the same logic, we get $D_{c2}^* = N\left(D_3^*\right) j_{c2}^*$ where j_{c2}^* is the $(k-1)\times 1$ eigenvector associated with the second largest eigenvalue of the matrix (26). The other 5 consumption residual innovations can be found in a similar way.

A.4 SDF with the IST News Shock and Consumption Residual Innovations

In this section, we show that the stochastic discount factor can be expressed in terms of the IST news shock and consumption residual innovations, and their consumption impulse responses.

Recall that the h-step ahead forecast error of y_t is a linear function of $u_t, u_{t+1}, \cdots, u_{t+h}$:

$$y_{t+h} - E_{t-1}\left[y_{t+h}\right] = \sum_{\tau=0}^{h} B_{h-\tau} u_{t+\tau} = \sum_{\tau=0}^{h} B_{h-\tau} \tilde{A}_0 D \varepsilon_{t+\tau}.$$

Consumption is the third variable in our VAR. Therefore, the h-step ahead impulse response of c_t following time-t shocks is

$$E_t\left[c_{t+h}\right] - E_{t-1}\left[c_{t+h}\right] = \mathbf{e}_3' B_h u_t = B_{3,h}\tilde{A}_0 D \varepsilon_t.$$

Here, $\mathbf{e}_3$ is a vector with one in the third place and zeros elsewhere, and $B_{3,\tau}$ is the third row of $k \times k$ matrix B_τ.

Suppose we do not identify the true identification matrix D, but instead identify another orthonormal matrix $\tilde{D}$. Since both D and $\tilde{D}$ are orthonormal matrices, there exists a $k \times k$ orthonormal matrix R that satisfies

$$\tilde{D} = DR.$$

The h-step ahead consumption impulse response can be restated in terms of $\tilde{D}$:

$$\begin{aligned} E_t\left[c_{t+h}\right] - E_{t-1}\left[c_{t+h}\right] &= B_{3,h}\tilde{A}_0 D \varepsilon_t \\ &= B_{3,h}\tilde{A}_0 D R R^{-1} \varepsilon_t \\ &= B_{3,h}\tilde{A}_0 \tilde{D} \epsilon_t, \end{aligned}$$

where ϵ_t is the orthonormal transformation of fundamental shocks ε_t using $R^{-1} = R'$:

$$\epsilon_t = R^{-1}\varepsilon_t.$$

In other words, $\tilde{D}$ is the identification matrix for ϵ_t. We can calculate ϵ_t as

$$\begin{aligned}\epsilon_t &= R^{-1}D^{-1}\tilde{A}_0^{-1}u_t \\ &= \tilde{D}^{-1}\tilde{A}_0^{-1}u_t.\end{aligned}$$

The unexpected change in the log stochastic discount factor following time-t shocks can also be expressed in terms of $\tilde{D}$ and ϵ_t :

$$\begin{aligned} s_{t|t-1} - E_{t-1}\left(s_{t|t-1}\right) &= -\left[E_t - E_{t-1}\right]\left(c_t - c_{t-1}\right) + (1-\gamma)\left[\left[E_t - E_{t-1}\right]\left(\sum_{h=0}^{\infty}\beta^h \Delta c_{t+h}\right)\right] \\ &= -B_{3,0}\tilde{A}_0 D\varepsilon_t + (1-\gamma)\sum_{h=0}^{\infty}\beta^h\left(B_{3,h} - B_{3,h-1}\right)\tilde{A}_0 D\varepsilon_t \\ &= -B_{3,0}\tilde{A}_0\tilde{D}\epsilon_t + (1-\gamma)\sum_{h=0}^{\infty}\beta^h\left(B_{3,h} - B_{3,h-1}\right)\tilde{A}_0\tilde{D}\epsilon_t. \end{aligned}$$

with $B_{3,-1} = \mathbf{0}_k'$. Therefore, if we know $\tilde{D}$ and ϵ_t instead of D and ε_t, we can still fully specify the log stochastic discount factor. Let $\tilde{D}$ contain the identification vectors for the IST news shock and the consumption residual innovations. Then, we can express the stochastic discount factor in terms of the IST news shock and the consumption residual innovations, and their consumption impulse responses. Note that if a consumption residual innovation has zero consumption impulse response, it does not enter the stochastic discount factor.

A.5 Linearization of Asset Pricing Model

From (13), we have

$$E\left[R_t^i - R_t^f\right] = -Cov\left(\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]}, R_{i,t} - R_{f,t}\right). \tag{27}$$

Note that the log linearization of $S_{t|t-1}\left(= \exp\left(s_{t|t-1}\right)\right)$ around $\log\left(E_{t-1}\left[S_{t|t-1}\right]\right)$ implies that

$$S_{t|t-1} \simeq E_{t-1}\left[S_{t|t-1}\right] + E_{t-1}\left[S_{t|t-1}\right]\left(s_{t|t-1} - \log\left(E_{t-1}\left[S_{t|t-1}\right]\right)\right),$$

which is rearranged into

$$\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]} \simeq 1 + s_{t|t-1} - \log\left(E_{t-1}\left[S_{t|t-1}\right]\right). \tag{28}$$

Since $s_{t|t-1}$ is normally distributed,

$$\log\left(E_{t-1}\left[S_{t|t-1}\right]\right) = \log\left(\exp\left(E_{t-1}\left[s_{t|t-1}\right] + \frac{1}{2}Var\left(s_{t|t-1}\right)\right)\right)$$
$$= E_{t-1}\left[s_{t|t-1}\right] + \frac{1}{2}Var_{t-1}\left(s_{t|t-1}\right). \tag{29}$$

Exploiting the homoskedasticity of $s_{t|t-1}$ and combining 28 and (29), we have

$$\frac{S_{t|t-1}}{E_{t-1}\left[S_{t|t-1}\right]} \simeq s_{t|t-1} - E_{t-1}\left[s_{t|t-1}\right] + b_0, \tag{30}$$

where b_0 is a constant. Section 6.3, shows that the shock to the log stochastic discount factor is reasonably well approximated as

$$s_{t|t-1} - E_{t-1}\left[s_{t|t-1}\right] \simeq b_{news}\varepsilon_{news,t} + b_1\epsilon_{1,t} + b_2\epsilon_{2,t}, \tag{31}$$

where b_{news}, b_1, and b_2 are some constants. Lastly, plugging (31) into (30), we can rewrite (27) as the linear factor model of

$$E\left[R_t^i - R_t^f\right] = Cov\left(b_{news}\varepsilon_{news,t} + b_1\epsilon_{1,t} + b_2\epsilon_{2,t} + b_0, R_{i,t} - R_{f,t}\right)$$
$$= b_{news}Cov\left(\varepsilon_{news,t}, R_{i,t} - R_{f,t}\right) + b_1Cov\left(\epsilon_{1,t}, R_{i,t} - R_{f,t}\right) + b_2Cov\left(\epsilon_{2,t}, R_{i,t} - R_{f,t}\right).$$

.

Figures

Figure 1: The IST News Shock and Realized Long-run Consumption Growth

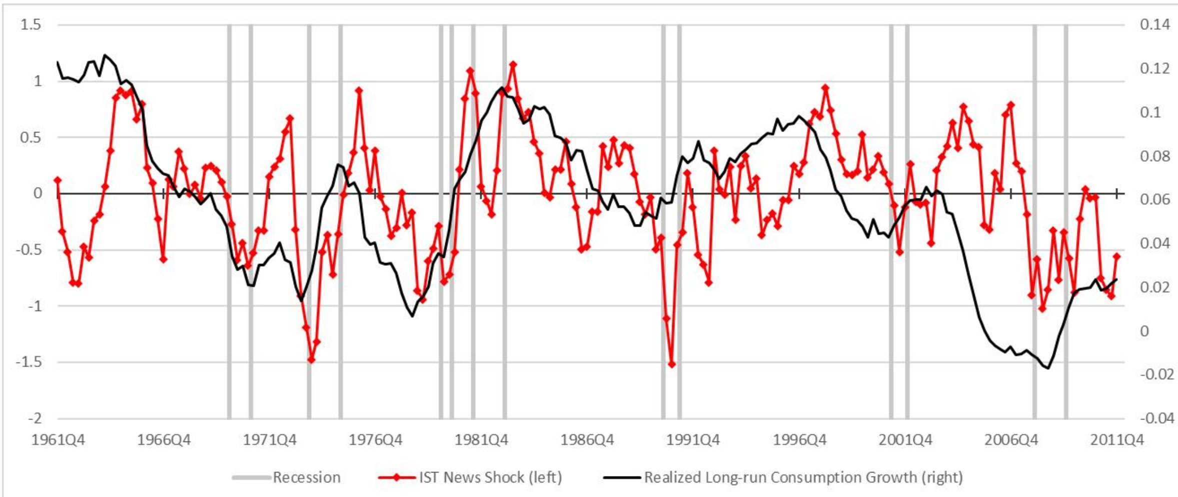
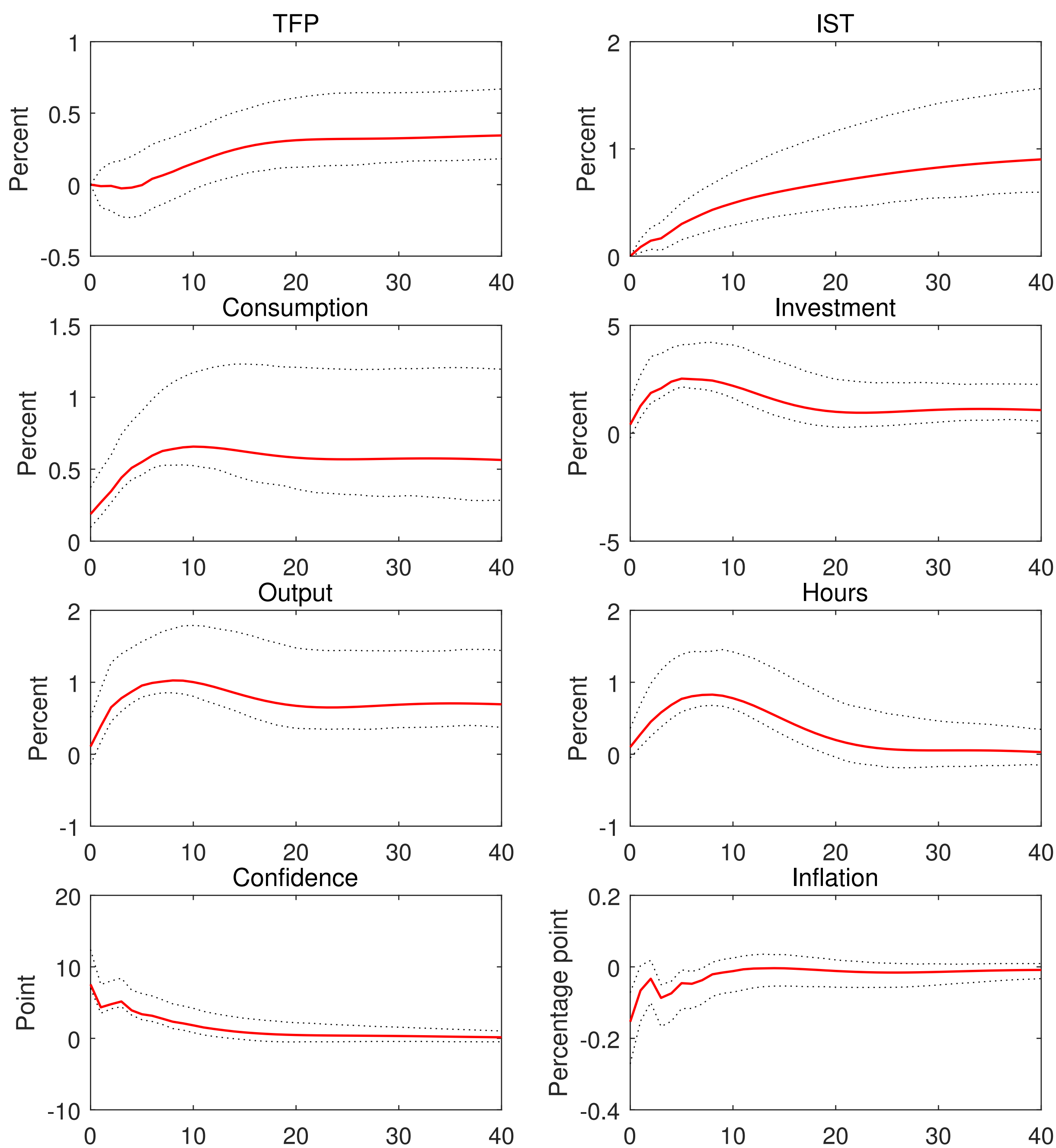


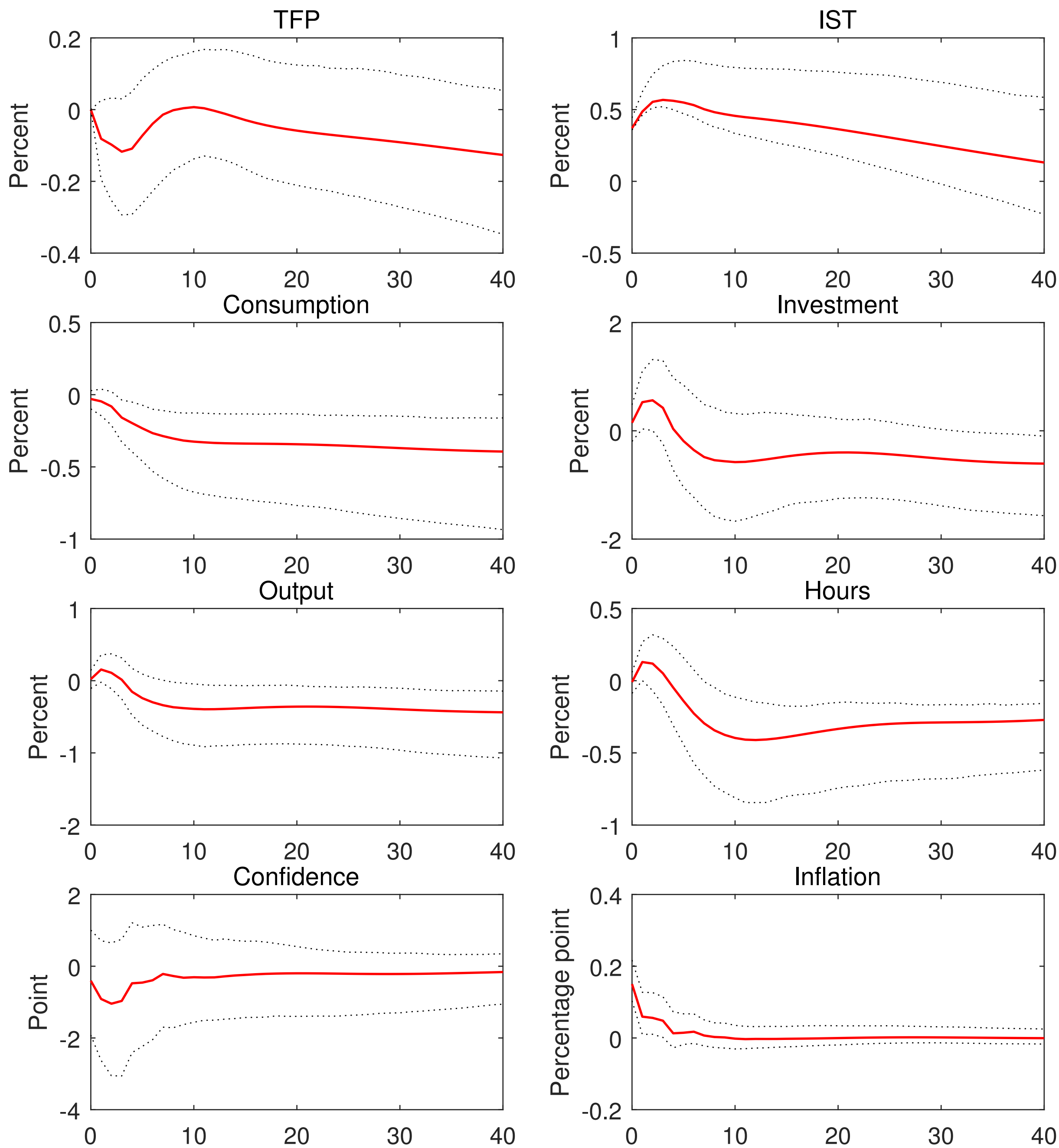
Figure 1 plots the four-quarter moving average IST news shock (left axis) and realized long-run consumption growth (right axis) in our sample period. The vertical lines represent the starting and ending points of NBER recessions. Realized long-run consumption growth for quarter t is calculated as the discounted sum of actual consumption growth over the next 16 quarters, $\left(\sum_{h=0}^{16} \beta^h \Delta c_{t+h}\right)$, with a discount factor of 5% per annum, $\beta = 0.95^{1/4}$, as in the work of Malloy et al. (2009). Sample includes quarterly data from 1961Q4 to 2011Q4.

Figure 2: Impulse Responses to the IST News Shock



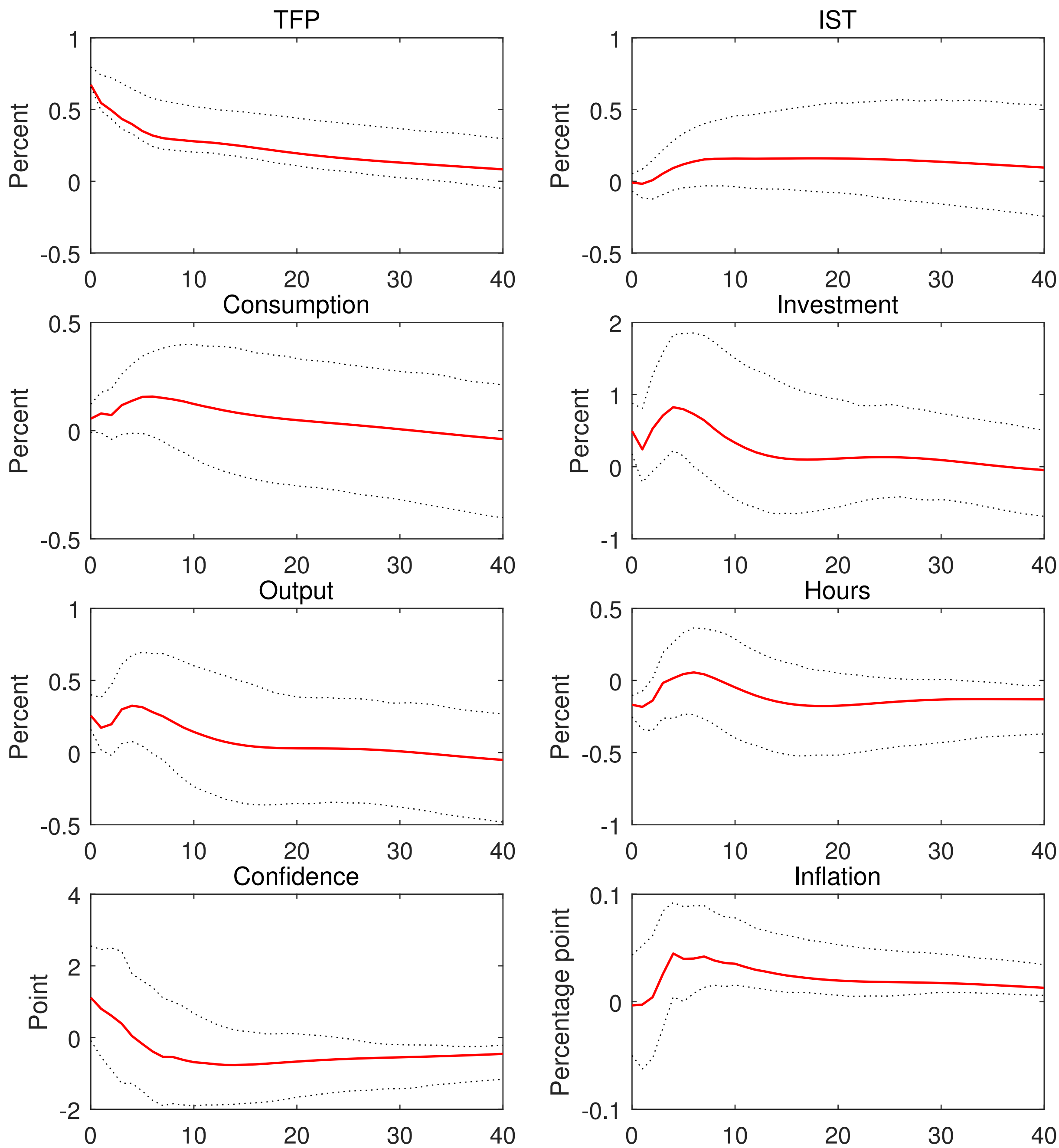
The solid line is the estimated impulse response to a one standard deviation IST news shock. The dashed lines are 1st and 99th percentile Hall (1992) confidence bands from 2,000 bootstrap replications of the reduced form VAR. X-axis is horizon in quarters.

Figure 3: Impulse Responses to the IST current Shock



The solid line is the estimated impulse response to a one standard deviation IST current shock. The dashed lines are 1st and 99th percentile Hall (1992) confidence bands from 2,000 bootstrap replications of the reduced form VAR. X-axis is horizon in quarters.

Figure 4: Impulse Responses to TFP current Shock



The solid line is the estimated impulse response to a one standard deviation TFP current shock. The dashed lines are 1st and 99th percentile Hall (1992) confidence bands from 2,000 bootstrap replications of the reduced form VAR. X-axis is horizon in quarters.

Figure 5: The Share of Forecast Error Variance Attributable to the Three Technology Shocks

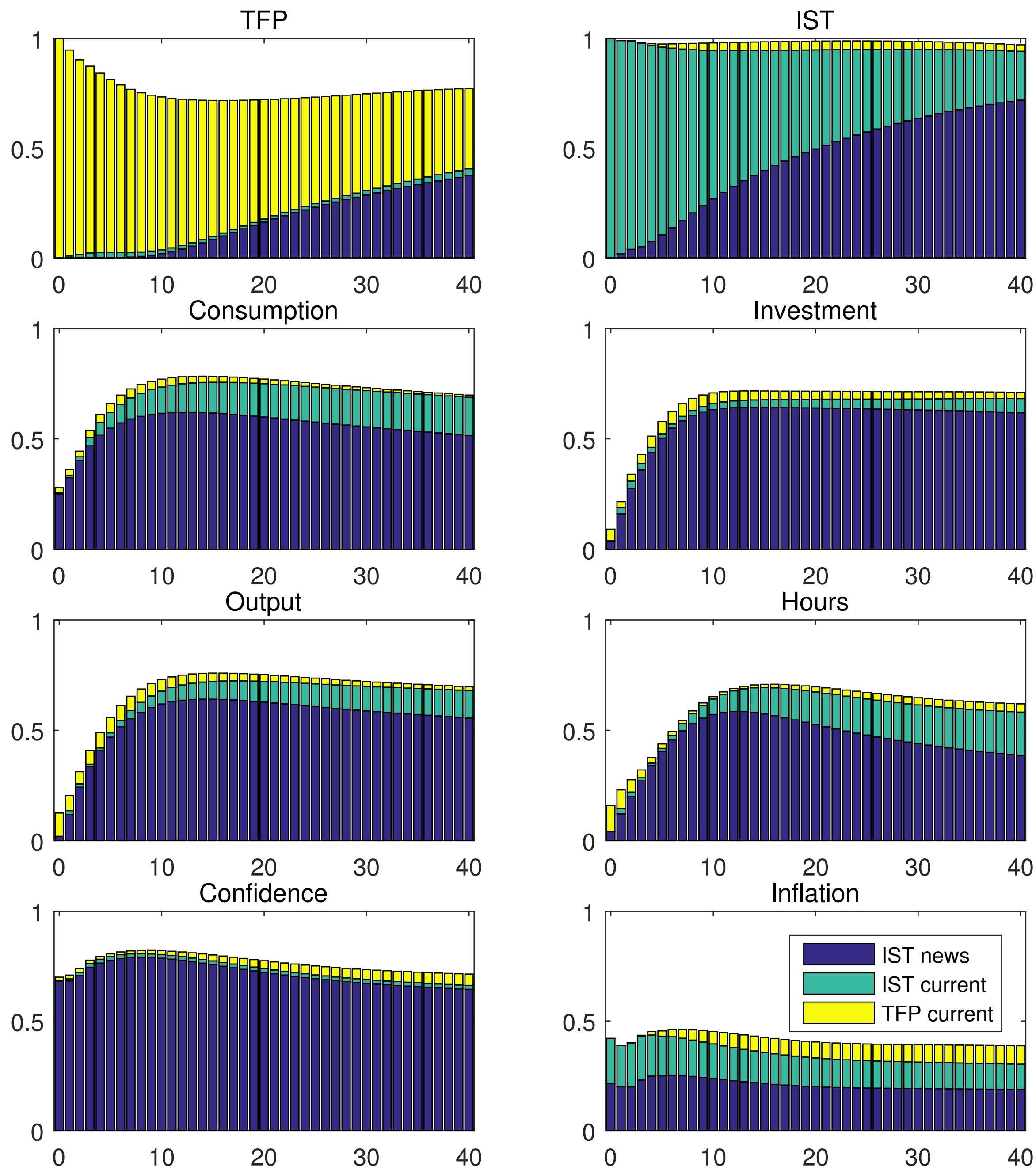
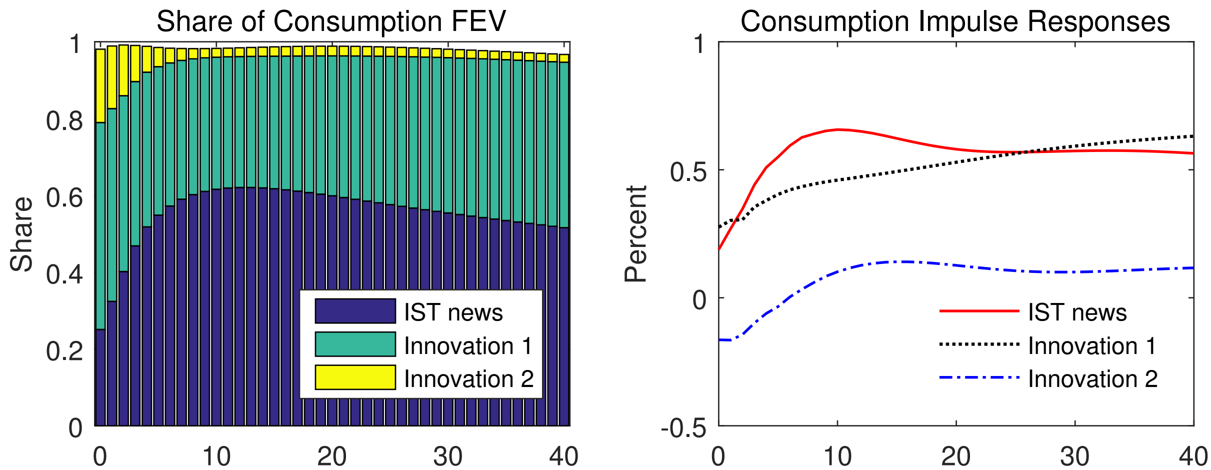


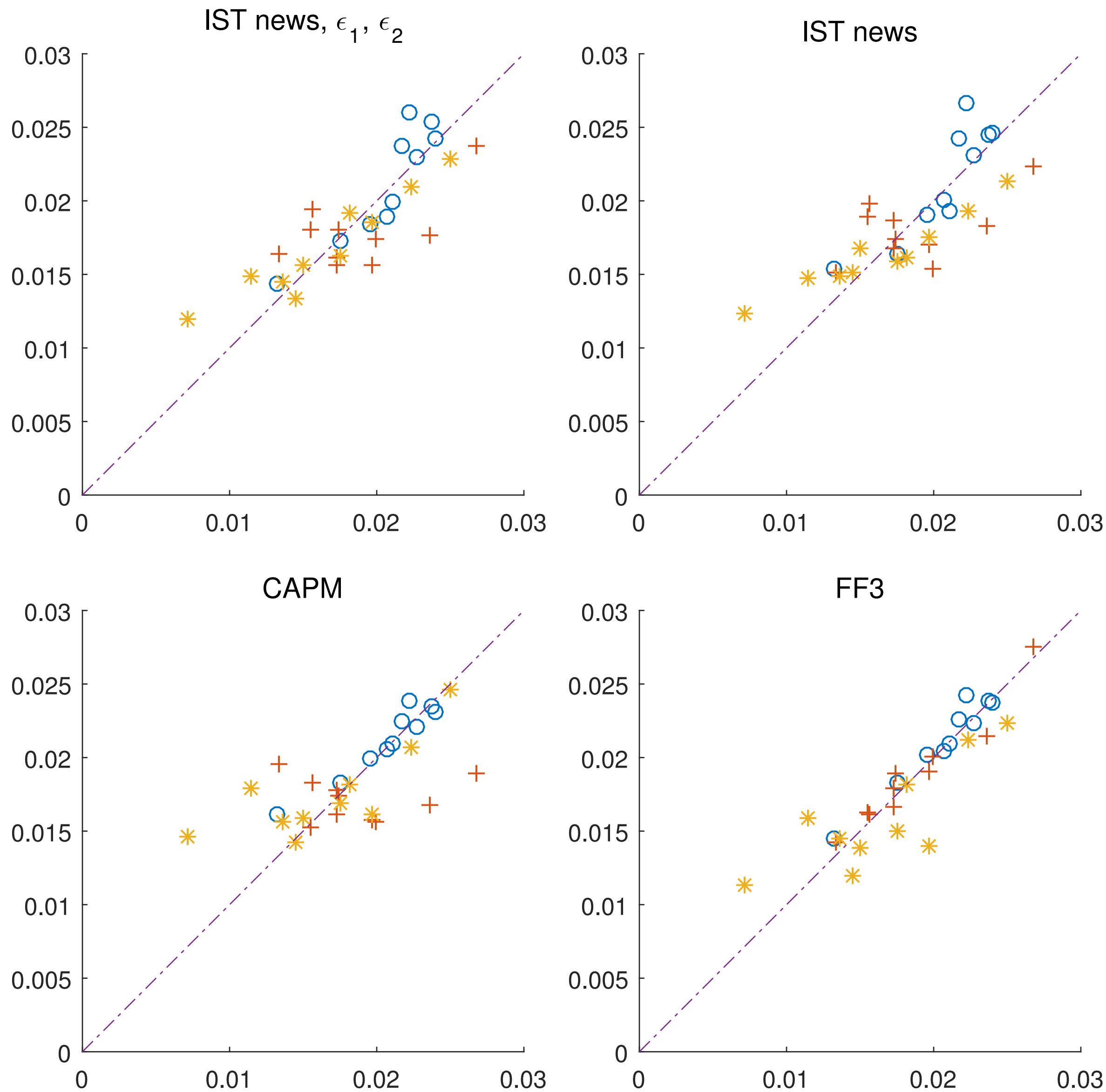
Figure 5 shows the cumulative share of the forecast error variance attributable to the IST news shock, the IST current shock, and the TFP current shock. Because there are unidentified structural shocks in the VAR, the cumulative share does not necessarily sum to one. X-axis is horizon in quarters.

Figure 6: Consumption Residual Innovations



The graph on the left shows the cumulative share of the forecast error variance of consumption attributable to the IST news shock and the first two consumption residual innovations. The graph on the right shows the impulse responses of consumption to the IST news shock and the first two consumption residual innovations. We identify the two consumption residual innovations as the first two principal components of residual consumption movements not accounted for by the IST news shock. X-axis is horizon in quarters.

Figure 7: Cross-Sectional Asset Pricing Test



We plot the average quarterly returns of 30 portfolios – 10 IST news shock beta sorted portfolios (o), 10 size sorted portfolios (+) and 10 BM sorted portfolios (*) against the fitted returns using four different models. The top left graph shows the pricing results of our three factor baseline model with the IST news shock and the two consumption residual innovations of ϵ_1 and ϵ_2. The top right graph shows the pricing results of the single factor model with the IST news shock. As benchmarks, we fit the returns using the CAPM and Fama-French three factor models and plot the results in the bottom two graphs.

Tables

Table 1: Consumption Growth Following the Three Technology Shocks

	Short-run Consumption Growth	Long-run Consumption Growth
IST news	0.0019	0.0056
	(3.144)	(3.400)
IST current	-0.0003	-0.0036
	(-1.109)	(-2.616)
TFP current	0.0006	0.0000
	(1.939)	(0.014)

Table 1 calculates changes in short-run consumption growth, $[E_t - E_{t-1}]\,(c_t - c_{t-1})$, and long-run consumption growth, $[E_t - E_{t-1}]\left(\sum_{h=0}^{\infty} \beta^h \Delta c_{t+h}\right)$, following a positive one standard deviation IST news shock, IST current shock, and TFP current shock based on the consumption impulse responses in Figure 2, 3, and 4. We approximate the change in long-run consumption growth as the change in the discounted sum of expected consumption growth over the next 40 quarters, $[E_t - E_{t-1}]\left(\sum_{h=0}^{40} \beta^j \Delta c_{t+h}\right)$. We assume $\beta = 0.95^{\frac{1}{4}}$ following Malloy et al. (2009). We report t-statistics in parentheses. t-statistics are based on the standard deviations of consumption growth from 2,000 bootstrap replications of the reduced form VAR.

Table 2: The IST News Shock and Realized Long-run Consumption Growth

	Moving Average Shocks		Current Quarter Shocks	
Intercept	0.059	0.059	0.059	0.059
	(6.948)	(6.978)	(6.996)	(6.985)
IST news	0.022	0.022	0.008	0.008
	(2.783)	(2.769)	(3.012)	(3.037)
IST current	-	-0.001	-	-0.001
	-	(-0.258)	-	(-0.733)
TFP current	-	-0.006	-	-0.001
	-	(-0.868)	-	(-0.639)
$Adj - R^2$	10.3%	10.2%	4.7%	4.%

Table 2 shows the results of regressing realized long-run consumption growth on the technology shocks. Realized long-run consumption growth for quarter t is calculated as the discounted sum of actual consumption growth over the next 16 quarters, $\left(\sum_{j=0}^{16} \beta^j \Delta c_{t+j}\right)$, with $\beta = 0.95^{\frac{1}{4}}$ as in the work of Malloy et al. (2009). In the left two columns, independent variables for quarter t are the four-quarter moving average technology shocks from quarter $t-3$ to quarter t. In the right two columns, independent variables for quarter t are the technology shocks at quarter t. Sample includes quarterly data from 1961Q4 to 2011Q4. We report t-statistics in parentheses. t-statistics are based on Newey-West HAC standard errors with 21 quarter lags for the left two columns and 17 quarter lags for the right two columns.

Table 3: Decile Portfolios Sorted on Betas with the IST news shock, the IST current shock, and the TFP current shock

Panel A: Decile Portfolios Sorted on IST News Shock Beta									
							Hi-Lo		
	Lo	2	3	8	9	Hi	ret	size	BM
μ	0.046	0.029	0.060	0.073	0.090	0.100	0.054	-1.068	-0.031
	(1.793)	(1.216)	(2.765)	(3.151)	(3.269)	(2.987)	(2.542)	(-5.13)	(-0.42)
Std Dev	0.197	0.161	0.171	0.193	0.218	0.262	0.172		
SR	0.231	0.178	0.352	0.376	0.412	0.381	0.316		
$\beta_{\texttt{IST news}}$	0.018	0.015	0.022	0.021	0.025	0.029	0.010		
	(2.274)	(2.279)	(3.127)	(3.134)	(3.731)	(3.322)	(1.625)		
$\beta_{\texttt{IST curr}}$	-0.003	-0.004	-0.004	-0.002	-0.007	-0.003	0.000		
	(-0.43)	(-0.68)	(-0.63)	(-0.22)	(-0.86)	(-0.28)	(-0.03)		
$\beta_{\texttt{TFP curr}}$	0.008	0.004	0.003	0.008	0.015	0.010	0.002		
	(0.868)	(0.491)	(0.451)	(0.925)	(1.653)	(0.920)	(0.375)		

Panel B: Decile Portfolios Sorted on IST Current Shock Beta									
							Hi-Lo		
	Lo	2	3	8	9	Hi	ret	size	BM
μ	0.068	0.060	0.073	0.072	0.063	0.087	0.020	0.173	-0.037
	(1.956)	(2.231)	(3.002)	(3.924)	(3.005)	(3.242)	(0.745)	(0.435)	(-1.66)
Std Dev	0.240	0.196	0.174	0.177	0.189	0.225	0.158		
SR	0.282	0.308	0.418	0.409	0.332	0.388	0.124		
$\beta_{\texttt{IST news}}$	0.032	0.019	0.021	0.019	0.021	0.029	-0.003		
	(3.206)	(2.669)	(3.668)	(2.823)	(2.639)	(3.441)	(-0.39)		
$\beta_{\texttt{IST curr}}$	-0.001	0.000	0.001	-0.006	-0.004	-0.002	-0.001		
	(-0.09)	(0.021)	(0.105)	(-1.00)	(-0.58)	(-0.22)	(-0.18)		
$\beta_{\texttt{TFP curr}}$	0.007	0.007	0.003	0.005	0.008	0.008	0.001		
	(0.684)	(0.781)	(0.403)	(0.574)	(0.977)	(0.792)	(0.243)		

Panel C: Decile Portfolios Sorted on TFP Current Shock Beta									
							Hi-Lo		
	Lo	2	3	8	9	Hi	ret	size	BM
μ	0.073	0.065	0.046	0.067	0.061	0.073	0.000	-0.370	-0.003
	(2.882)	(3.173)	(1.938)	(2.875)	(2.630)	(2.275)	(0.003)	(-0.95)	(-0.04)
Std Dev	0.206	0.172	0.163	0.182	0.192	0.241	0.177		
SR	0.354	0.381	0.285	0.371	0.319	0.304	0.001		
$\beta_{\texttt{IST news}}$	0.023	0.017	0.016	0.020	0.022	0.024	0.000		
	(3.149)	(2.517)	(2.575)	(2.811)	(3.315)	(2.706)	(0.071)		
$\beta_{\texttt{IST curr}}$	0.001	-0.002	-0.003	-0.004	-0.006	-0.001	-0.001		
	(0.109)	(-0.38)	(-0.50)	(-0.56)	(-0.88)	(-0.07)	(-0.24)		
$\beta_{\texttt{TFP curr}}$	0.006	0.007	0.004	0.009	0.009	0.010	0.004		
	(0.713)	(0.902)	(0.597)	(0.971)	(0.869)	(0.967)	(0.576)		

Table 3 reports quarterly average excess returns and post-ranking betas of 10 portfolios sorted on the pre-ranking beta. μ, Std Dev, and SR are annualized. The pre-ranking betas of individual stocks are estimated using the previous 20 quarterly observations at the beginning of each quarter. The portfolio formation starts at the beginning of 1966Q1 and ends at the end of 2015Q4, resulting in 200 quarterly portfolio return observations. In the last two columns, the average differences in size (ranks from 1 to 10 using French's size breakpoints) and BM (book-equity to market-equity ratio) between top and bottom decile portfolios are reported. We report t-statistics in parentheses. t-statistics are based on Newey-West HAC standard errors with 21 quarter lags.

Table 4: Future Cash Flow Growth of Portfolios Sorted on IST News Shock Beta

Panel A : Sales Growth							
Decile	Lo	2	3	8	9	Hi	Hi-Lo
Intercept	0.103	0.092	0.097	0.113	0.115	0.169	0.066
	(3.752)	(3.880)	(4.624)	(5.756)	(5.268)	(5.944)	(2.017)
IST news	-0.066	0.016	0.001	0.043	0.072	0.094	0.160
	(-1.415)	(0.338)	(0.036)	(1.266)	(2.417)	(1.879)	(3.428)
R^2	4.5%	0.5%	0.0%	4.3%	7.4%	8.7%	16.4%
Panel B : Operating Income Growth							
Decile	Lo	2	3	8	9	Hi	Hi-Lo
Intercept	0.086	0.071	0.074	0.121	0.116	0.208	0.105
	(2.532)	(2.847)	(2.652)	(3.454)	(4.024)	(6.552)	(2.917)
IST news	-0.048	0.020	0.065	0.067	0.108	0.095	0.161
	(-1.142)	(0.387)	(2.287)	(1.172)	(2.477)	(2.261)	(2.714)
R^2	1.1%	0.4%	3.7%	3.5%	8.2%	5.9%	12.9%

Table 4 shows the results of regressing future sales (Compustat item SALE) and operating income (Compustat item OIBDP) growth of IST news shock beta sorted portfolios on IST news shock. The dependent variable is the future three-year sales (operating income) growth of portfolios in June of each year. The independent variable is the past 4-quarter moving average of the IST news shock in June of each year. The future three-year sales (operating income) growth of a portfolio in June of year t is the log growth of total real sales (operating income) of firms in the portfolio between fiscal year $t-1$ and fiscal year $t+2$. Among firms in the portfolio, only those with both fiscal year $t-1$ and $t+2$ sales (operating income) observations are included in the sales (operating income) growth calculation. Sales (operating income) in fiscal year $t-1$ is deflated by the nondurable and service consumption deflator in calendar year $t-1$. Sample includes annual data from 1966 to 2015. We report t-statistics based on Newey-West HAC standard errors with 4 year lags in parentheses.

Table 5: Euler Equation Estimation for Portfolios Sorted on IST News Shock Beta

	Model 1 IST news, ϵ_1, ϵ_2	Model 2 IST news, ϵ_1	Model 3 IST news
	Panel A : Unrestricted		
α	-0.003	-0.002	-0.003
	(-0.364)	(-0.270)	(-0.325)
γ	92.243	91.098	130.499
	(1.994)	(2.077)	(2.181)
R^2	73.6%	73.6%	70.6%
J-test	6.363	7.097	4.127
	(0.393)	(0.474)	(0.155)
	Panel B : Restricted ($\alpha = 0$)		
γ	80.7330	82.4861	117.9117
	(2.237)	(2.215)	(2.452)
R^2	71.7%	72.5%	69.2%
J-test	12.663	15.797	4.529
	(0.822)	(0.929)	(0.127)

Table 5 shows the results of estimating the Euler equation (13) for 10 portfolios sorted on IST news shock beta. Estimation is by generalized method of moments using the identity weighting matrix. Panel A reports regressions of the average excess return of the 10 IST news beta sorted portfolios on a constant term (α) and the covariances of portfolio excess returns and the normalized stochastic discount factor (12). Panel B reports the same regressions without a constant term, imposing $\alpha = 0$. Model 1 assumes that the stochastic discount factor includes the IST news shock and the two consumption residual innovations. Model 2 assumes that the stochastic discount factor includes the IST news shock and the first consumption residual innovation. Model 3 assumes that the stochastic discount factor is determined by the IST news shock only. We report t-statistics for α and γ based on Newey-West standard errors with 21 quarter lags in parentheses. We also report the cross-sectional $R^2$and the J-test of over-identifying restrictions along with the p-values for the J-test in parenthesis. Sample includes quarterly data from 1965Q1 to 2015Q4.

Table 6: Cross-sectional Test with the IST News Shock

Panel A: Models with IST News Shock					
	Model 1	Model 2	Model 3	Model 4	Model 5
$\lambda_{\texttt{IST news}}$	0.603	0.604	0.629	0.485	0.592
	(2.089)	(2.093)	(2.166)	(1.868)	(2.019)
λ_{ϵ_1}	0.226	0.189	-	-	-
	(0.812)	(0.705)	-	-	-
λ_{ϵ_2}	0.105	-	-	-	-
	(0.394)	-	-	-	-
$\lambda_{\texttt{IST curr}}$	-	-	-	0.265	-
	-	-	-	(0.593)	-
$\lambda_{\texttt{TFP curr}}$	-	-	-	0.309	-
	-	-	-	(1.633)	-
$\lambda_{\texttt{MKT}}$	-	-	-	-	0.015
	-	-	-	-	(1.499)
MAPE	0.002	0.003	0.003	0.005	0.003
Adj-R^2	0.623	0.624	0.609	0.679	0.608

Panel B: Benchmark Models					
	CAPM	FF3	-	-	-
$\lambda_{\texttt{MKT}}$	0.019	0.006	-	-	-
	(1.833)	(2.579)	-	-	-
$\lambda_{\texttt{SMB}}$	-	0.005	-	-	-
	-	(1.043)	-	-	-
$\lambda_{\texttt{HML}}$	-	0.006	-	-	-
	-	(1.427)	-	-	-
MAPE	0.003	0.012	-	-	-
Adj-R^2	0.443	0.802	-	-	-

Table 6 reports the results of estimating the risk premium on IST news shock beta in the cross section of 30 portfolios – 10 IST news shock beta sorted portfolios, 10 size sorted portfolios and 10 BM sorted portfolios. Panel A considers five models with the IST news shock as a risk factor. Model 1 refers to our three factor baseline model with the IST news shock and two consumption residual innovations of ϵ_1 and ϵ_2. Model 2 considers an alternative two factor model with the IST news shock and the first consumption residual innovation. Model 3 considers the single factor model with the IST news shock. Model 4(5) considers the current shocks (market excess returns) as potential missing factors. Two benchmark models with traded factors of the CAPM and FF3 are examined in Panel B. t-statistics are reported in parentheses and adjusted by Shanken's correction.